

BOTSWANA INTERNATIONAL UNIVERSITY
OF SCIENCE & TECHNOLOGY

ASSESSMENT OF UNDERGROUND MINE PRODUCTION EFFICIENCY AT MORUPULE COAL MINE

BY

OTSWELETSE MOSIAMISI
STUDENT NUMBER: 12000687

MEng MINING ENGINEERING

A THESIS SUBMITTED TO THE FACULTY OF ENGINEERING AND TECHNOLOGY IN FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ENGINEERING IN MINING ENGINEERING OF BIUST

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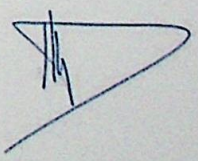
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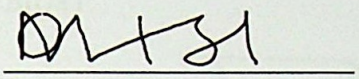


PROF. RAYMOND S. SUGLO

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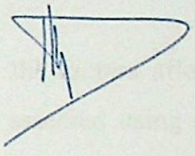
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CERTIFICATION

The undersigned certifies that he has read and hereby recommends for acceptance by the Faculty of Engineering and Technology a dissertation/thesis titled **Assessment of Underground Mine Production Efficiency at Morupule Coal Mine** in fulfilment of the requirements for the degree of Master of Engineering in Mining Engineering of the BIUST.



June 22, 2021

Prof. Raymond S. Suglo (Supervisor)

Date

ABSTRACT

Mining productivity is a measure of the effectiveness of mining resource inputs computed as a ratio of production output per input resources. Factors affecting productivity can be grouped as a combination of technical and economic factors. The ratio of the production outputs to inputs in a mine determines the mine's productivity. The greater the output produced at optimum cost, the more efficient is the functional mine system.

In this study, the factors affecting mine production efficiency at Morupule Coal Mine (MCM) were assessed using statistical analysis methods as the mine has varying daily production levels that are mostly below set threshold targets. Also, production shift variances were assessed and the causes of productivity variances were classified according to scale of impact. The results show wide variances in the production outputs between morning, afternoon and night shifts; the equipment availabilities for continuous miners (CMs) ranged from 79.5% to 92.2% and those for shuttle cars varied from 84.0% to 92.0%. The average engineering availabilities for CMs and shuttle cars were generally higher than their set threshold targets but they are the lowest performing equipment's. The regression models show a high goodness of fit between the parameters and mine production showing that there is a strong correlation between them.

It is recommended that the CMs should be frequently examined to be within their equipment reliability period and the duration of the mean time to repair of shuttle cars should be improved to ensure they are serviced within the maintenance service threshold targets.

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CHAPTER 1

INTRODUCTION

1.1 Background

Mining productivity is a measure of the effectiveness of mining resource inputs computed as a ratio of production output per input resources. Productivity is defined as a single factor, multi-factor and total factor productivity (Tsolas, 2019). Factors affecting productivity can be grouped as technical, economic and a combination of economic and technical factors.

Humphreys (2019) states that mining productivity is inherently cyclical as evidenced during mining boom seasons. Generally, during periods of higher commodity prices mining entities focus on volume while productivity declines and during periods of low prices, they focus on maximisation of resource utilisation.

A mining boom season is characterised by a decline in productivity as production efficiency is neglected to have high returns. Consequently, the cost for production gradually increases (Hall and Hall, 2015) and commodity prices gradually drop with time and investor confidence drops from high to low. As a result, in the past during periods of mining booms, the focus of the mining industry shifts to maximising productivity to address gradual commodity price drops, decline in investor confidence and escalation in production inefficiencies. This means that during periods of high commodity prices mining performance may be overlooked or neglected as profit margins are high and these eventually cost the company when the prevailing conditions change. Therefore, high operational performance of mining processes across distinct production faces need to be maintained based on the scale of production and prevailing conditions (e.g. change in mineral market price and technology).

Today, productivity is a topical issue in operating mines and is set as a work priority by mining entities globally (Ernst and Young, 2014). Productivity is a challenge to most mining companies. Mining productivity assessment plans must be set to check the effectiveness of the operational processes and resource input utilisation to cater for declining production under the prevailing conditions. Production evaluation is necessary as conditions such as

mine plans and available resources for use change with time. Also, the conditions of input resources for work deteriorate with time. As such improvement strategies to either increase/decrease production output, reduce cost and bottlenecks can be implemented using the same resources and increasing/decreasing input resources.

This study is distinctive due to the use of actual data from an operating underground mine. The results will show challenging/experienced conditions in an underground mine and lead to real solutions/ measures to improve mining productivity. The proposed solutions can apply to other mines and bring benefits such as process improvement and better utilisation of resources. This study on production assessment contributes to the literature on key focus areas such as resource management and operational research, which ensures the mining industry's sustainability.

1.2 Problem Statement

The ratio of the production outputs to inputs in a mine determines the level of operational efficiency which is known as mine productivity. The greater the output produced at optimum cost, the more efficient is the functional mine system. Productivity is also defined as the annual production of a mineral resource per person or piece of equipment employed (Dias and Aparicio, 2018).

Production rate efficiency may be at a minimum due to factors affecting productivity such as the cycle of operations, machine efficiency and manpower (Mishra *et al.*, 2013). Low levels of efficiency lead to increased production cost and more time lost. Therefore, the mine will not have high outputs from the resources invested and the operations will be at a lower scale of economy.

In a global survey where the participants were mine executives, it was concluded that productivity is the main challenge in the mining field and this was listed on the management agenda (Ernst and Young, 2014). It was noted that it is a challenge for mines to operate at high scale as some operations may be conducted at what is termed "diseconomies of scale". The intent is to grow the mine's operations capability to maximum economies of scale. For mines to operate at maximum scale the challenges of productivity must be addressed to ensure effective use of resources and higher turnover. Also monitoring and review must be

done continuously throughout the mine life as changes occur which affect productivity levels of the equipment and machines in the system.

Production in a mine is affected by various factors which should be investigated to improve mine production and use the input resources efficiently (Mishra *et al.*, 2013). Identification of measures of productivity is important as the mining processes must be evaluated periodically to establish standard operational targets for all factors of mine production.

This research attempts to study the factors affecting mine production at Morupule Coal Mine (MCM) as the mine is experiencing challenges in achieving optimal production performance. This is evident by varying daily and monthly production levels that are mostly below set threshold targets. MCM's suboptimal performance shows possible existence of production uncertainties which may be critical input resources and maintenance service performances. MCM is the only supplier of coal to Morupule Power Station which generates more than two thirds of Botswana's electricity consumption and other entities in the country. Suboptimal production brings uncertainties to the coal buying entities and affect those dependent on the buyers' services.

1.3 Objectives of Research

The objectives of this study are to:

1. Identify the factors affecting mine production at Morupule Coal Mine (MCM).
2. Assess the variances in production during shifts against the established targets at MCM.
3. Identify causes of production losses and classify the causes of productivity variances according to scale of impact.
4. Identify and propose measures that will lead to achievement of set production targets.

1.4 Expected Outcomes

The outcomes of this study are:

i) Identification of factors that significantly affect mine productivity and the level of their impact on productivity.

ii) Maximum utilisation of resources will be achieved.

iii) Efficient and cost-effective operations will be developed to meet the projected production targets of the mine during the mine life.

1.5 Methods Used

The methods used in this study include:

i) Literature review on factors contributing to mine productivity measures.
ii) Mine visits for familiarisation with the mining operations.
iii) Field work to collect data for the study.
iv) Consultations and interviews with mine officials to gain first-hand information about the mining operations and processes.
v) Analysis of data using statistical and analytical methods.

1.6 Facilities Used

The facilities used in this study include library, computer and laboratory facilities in BIUST and Morupule Coal Mine.

1.7 Report Organisation

Chapter 1 contains the background of the study, problem statement and methods used while Chapter 2 contains the general information about the Morupule Coal Mine. Chapter 3 has the literature review on factors affecting mine productivity, technical function of production and measures of mining productivity. Chapter 4 has the data collection and analysis while Chapter 5 has the conclusions and recommendations arising from this study.

CHAPTER 2

GENERAL INFORMATION ABOUT MINE

2 INTRODUCTION

This chapter contains the general information about Morupule Coal Mine on the history, local geology, production and mineral processing operations of the mine.

2.1 History of Morupule Coal Mine

Morupule Coal Mine (MCM) is an underground coal mine located on the outskirts of Palapye along the Serowe-Palapye main road (A14), within the Central District of the Republic of Botswana. Figure 1 shows the location of the mine. MCM geographical coordinates are 22° 30' 46.9" S, 27° 01' 22.2" E.

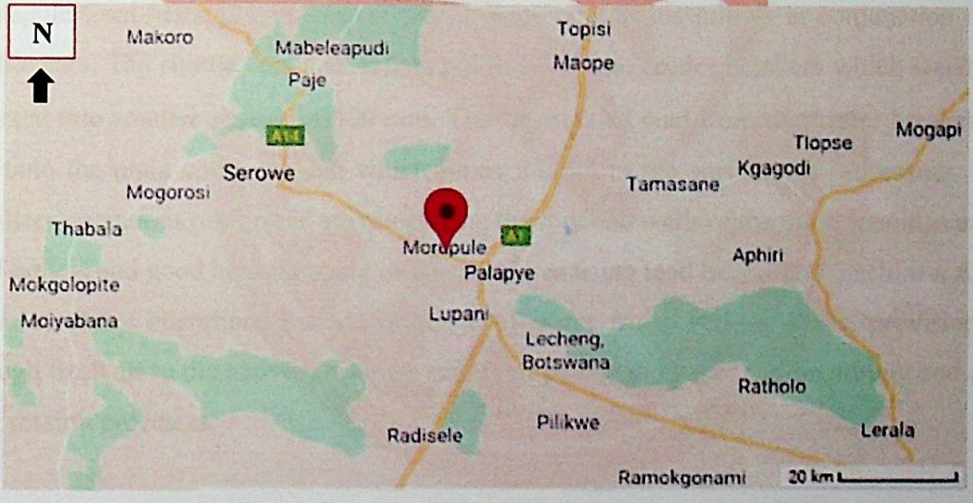


Figure 1 Location of Morupule Coal Mine (Anon., 2021a)

The mine commenced its production in 1973 and was owned by Anglo-American Corporation subsidiary. In 1973 the annual coal production was about 32,732 tonnes but this increased to 2,084,571 tonnes in 2015 due to market demands. In 2000 the mine was sold to Debswana Diamond Company (Pty) Ltd. Today the mine is wholly owned by the Government of Botswana and managed by a government-owned entity called Mineral Development Company Botswana (Pty) Ltd. (Anon., 2019a).

MCM extracts coal using room and pillar mining method. The coal products from the mine are sold to industries and service entities to produce energy and as a reductant for ferrochrome smelting. The major entities supplied with coal by MCM are Botswana Power Corporation plant, Makoro Bricks and Tiles, Botswana Ash, Botswana Meat Commission, Kgalagadi Breweries Limited and hospitals. Also, the mine supplies neighbouring countries such as Zambia, Zimbabwe, South Africa and Namibia with coal.

2.2 Local Geology

The geology of the Morupule area is of Karoo sedimentary rocks which consist of coals, shales and ecca sandstones of lower to middle size. The geology of the area is part of the major Karoo basin on the eastern part developed to the West of Morupule (Anon., 2019a). The coal seam in MCM is classified as low to average grade sub-bituminous coal.

2.3 Underground Mining Operations

Morupule Coal Mine (MCM) extracts coal using continuous miners in conjunction with shuttle cars. The shuttle cars haul and dump the coal into feeder breakers which fragment the coal into smaller sizes of ≤ 300 mm. The fragmented coal from the feeder breakers is fed unto the main conveyor belt which sends the ore to the surface for processing. The ancillary operations performed are reinforcing the roof and walls of the mine openings using roof bolters and good housekeeping of the work area using load haul dump machines. Also, some auxiliary operations include drainage of water from working areas, provision of enough fresh air to the active workings, supply of power and water for the mining and dust suppression processes.

MCM has four underground operating production sections. Each section has one CM, a roof bolter, three shuttle cars, a feeder breaker and conveyor belt linked to the main conveyor belt conveying raw coal to the mine stockpile on the surface (RoM). In total there are five CMs, four operating at different sections while one is on maintenance service. The continuous miners are placed on rotational maintenance services to ensure that whenever one CM is on maintenance others are actively operational. The cycle of operations of the CM at MCM consists of cutting, loading simultaneously into the shuttle cars and occasionally waiting for shuttle cars while that of the shuttle cars comprise being loaded, hauling (loaded), unloading (dumping) the coal materials into the feeder breaker and

returning (empty) to the CM location, waiting and positioning itself for loading by the CM. The CM usually advances 12 m into a panel face before it is moved to another face for cutting while roof bolting is done on the previous face.

The underground production team at each section of MCM consists of a ventilation attendant, two roof bolters, relief operator, three shuttle car operators, two CM operators, miner-in-charge and a shift boss who supervises two sections at a time in a shift. The total number of personnel in one shift is a key parameter in computing the coal mine productivity. Coal mine productivity in MCM is measured as the ratio of clean tonnes of coal the underground mine produces per employee hour.

2.4 Surface Mine Processing Operations

At the Processing Plant, the coal is fed into primary and secondary crushers to reduce it to sizes at most 75 mm and 32 mm respectively. The run of mine coal is processed using a Dense Medium Separator to wash the coal and separate it based on its calorific value. The separated coal is classified into different sizes. The mine products include raw and clean coal products which are raw coal, nuts, cobbles, fines, peas and filter cake (Anon., 2019a).

CHAPTER 3

LITERATURE REVIEW

3 INTRODUCTION

This chapter contains the literature review on mining productivity, production improvement techniques and analysis methods.

3.1 Production Efficiency

The efficiency of a production unit is a comparison between the actual values of its output and input (Lovell, 1993). A 100% efficiency means that a production process has achieved the maximum amount of output that is physically achievable with current technology or processes and given a fixed amount of inputs (Lawrence and Diewert, 1999). Production efficiency enables mine management to re-evaluate the mine's strategies, plans and practices to achieve high output values with minimal input resources.

The effectiveness of a mining production system expresses the level of resource utilisation (Honglan *et al.*, 2014). Mining efficiency aims to ensure that the supply and demand ratio is balanced at the current market prices, input resources are efficiently utilised, mining costs are minimised and profits maximised.

The production operations in mining include fragmentation and materials handling of ore and waste. The unit mining operations in surface mining are drilling and blasting or cutting, loading, hauling and dumping of either the ore or waste. For underground mines, the unit operations may differ depending on the methods utilised (e.g. use of continuous miner or longwall system in underground coal mines), ventilation and ground support requirements. Various factors influence mine production efficiency (Topp *et al.*, 2008; Elevli and Elevli, 2010; Fourie, 2016). The magnitude of these factors either minimise or maximise production and their measures give an indication to the mine planning and management team the need to maintain or change and implement strategies to achieve the set production targets.

The reliability of production factors depends on valid, accurate, complete and timely data. Consequently, good mine planning decisions have to be made to enable a mining company to achieve high production performance with optimised input resources in a timely manner. Maximum utilisation of the input resources increases the mine's productivity and ensures higher returns on investment for the mining company. With profits the mining entity can explore other avenues to increase the mine's life such as increased exploration for more reserves.

Production efficiency has technical and allocative aspects (Reiff *et al.*, 2002). The technical aspects are determined by the ratio of output units to input units and deal with the capability to utilise given production unit inputs effectively to produce maximal output units. The allocative aspect is the ability to combine inputs and outputs in optimal proportions in the light of prevailing market prices. A combination of technical and allocative efficiency analysis indicates the economic efficiency of an industrial process. Mine production efficiency may either be periodically assessed on technical, allocative or economic efficiency levels to indicate production performance and potentially show variances in outputs as the scale of production fluctuates with time.

According to Fried *et al.* (2008) variances in the production results may be attributed to differences in the technology applied, scale of production, operational efficiency and the environment where the production takes place. Therefore, the production variances must be evaluated to maintain or define a scale of production by assessing the existing aspects of production. This will ensure that appropriate measures are taken to monitor the scale of production.

3.2 Technical Function of Production

Production function refers to the maximum output levels that can be achieved with a given amount of input using a given production technology, processes or operations (Berck and Helfand, 2014). It is also described as a relationship between the output volumes produced per input volume change. The production function is given by equation (1) where there are one or more variable inputs:

$$Y = f(X_1, X_2, \ldots, X_n) \quad (1)$$

Where Y is production output while $X_0, X_1, X_2, \ldots, X_n$ are inputs variables in the function.

The inputs to the production function are known as factors of production as they contribute to the efficiency of the production operations. These are parameters which can be strategically planned and controlled to achieve maximum production efficiency. As such production analysis needs to be carried out to optimise the scale of production to ensure that there are no variances in production levels from the set targets so as not to hamper the company's production performance. Production levels below the targeted values are likely indicators of the inefficiencies in the invested resources. The measures of production efficiency are production success indicators which lead to the identification of controllable and uncontrollable sources that cause production variances (Fried *et al.*, 2008).

3.3 Measures of Mining Productivity

The productivity of an operation is measured using either a single or multi-factor productivity (Mawson *et al.*, 2003). Single factor productivity, which is also known as partial factor productivity, is a measure of production output per a unit measure of a single resource input e.g. labour productivity, equipment productivity or capital productivity. Multi-factor productivity is a description of production output per a grouped units' measure of resource inputs in a production system. Also, total factor productivity computation can be applied, which refers to a measure of total output per all resource inputs not per grouped input units as in multi-factor productivity.

3.4 Determinants of Underground Coal Mine Productivity

Many factors determine the level of mine production. These include the type of equipment used, quality of labour, available capital, energy sources, nature of working environment, work practices and availability of raw materials. Productivity reflects the degree of utilisation of the production factors (Honglan *et al.*, 2014). According to Topp *et al.* (2008) the factors that determine production efficiency are technology, management, skills and work practices. Fourie (2016) defines the factors affecting productivity in mining as the selection of appropriate equipment, operator competency, haul profiles and work scheduling including the short-term to long-term planning by the management.

Numerous factors influence an underground coal miner's productivity. These factors include seam thickness, mine roof and floor conditions, annual production capacity, period of operation, quality of the finished product (coal preparation), presence of water, the

quantity of methane and/or strata gases emitted, management philosophy and mining equipment performance (Malhotra, 1975). Other factors that affect underground coal mining productivity are availability of skilled personnel, demographics shift and regulatory inspection (Kuykendall and Qureshi, 2014). Also, occupational health and safety status of an underground coal mine influence production.

3.4.1 Mining Equipment Performance

The level of equipment operational efficiency affects the mine's productivity. The factors that affect the equipment performance are availability, state and repair period, and utilisation of the equipment. Also included is the availability of backup equipment to take care of sudden and unplanned equipment breakdowns. Operational factors such as resource utilisation and equipment cycle times must be assessed by applying appropriate performance analysis techniques to improve production levels (Elevli and Elevli, 2010).

Variations in the performance of mining equipment can also be attributed to varying natural conditions, equipment age, skill level of machine operators, machine capacity and the mining method used (Malhotra, 1975).

Machine availability and utilisation are key factors that influence mining equipment productivity. Availability and utilisation of equipment is critical to the level of mine productivity and lead to production improvement and the establishment of effective monitoring methods based on current performance. Machine capacities must be assessed to know their production rate (per hour or per shift) and compare them with the profiled machine characteristics.

Generally, the efficiency of a CM in a mining operation is dependent on the number of allocated shuttle cars, the length and conditions of haul roads, operator skills, shift downtime characteristics and the machine's operational age (Lashkari, 2014). The production performance of a CM is dependent on the haulage system in use (Winkel, 2003). The efficiency of the haulage system in turn either increases or decreases the cycle time of coal panel advance. CM cutting rate and down times affect mine productivity. The mean cycle time depends on the haulage distance to the feeder breakers and the operating conditions of the shuttle cars. Very short or long haulage distances often result in shuttle cars waiting on the CM or vice versa. This leads to unproductive times from the waiting times of shuttle

cars or CMs. Unproductive times in a continuous miner system lead to low effective cutting rates or lower operational hours by the CM during the available shift hours.

The early and late sump times of CM during an operational shift influence the production output. Generally, late starts and early stops in a shift reduce the production output per production inputs used. This leads to a decrease in the overall productivity of the mine production. Also, frequent changes of the CM from one face to another during a shift results in delays and more time spent in setting up the CM at the new face.

According to Jemishkumar *et al.* (2017) the productivity of a continuous miner system can be maximised in the following steps:

1) Maximising individual equipment performance.
2) Careful choice of mine production plans, roadway and equipment layout.
3) Equipment utilisation time.

The utilisation of shuttle cars can be influenced by varying factors or conditions such as (Lashkari, 2014):

1) Inadequate road maintenance which may lead to lower speeds and increased cycle times.
2) Inadequate equipment maintenance hence poor equipment conditions.
3) Inadequate skilled operators or inefficient operational management.
4) Frequent machine breakdowns requiring maintenance.
5) Ore cutting and roof support performed in dangerous grounds/production face adding more time to the cutting cycle and limiting the materials handling operations.

The lengths of the cycle times of shuttle cars can show the inefficiencies in the materials handling system that need evaluation to identify the root causes. A time study of a CM system can be used to evaluate and optimise the number of shuttle cars allocated to a CM.

Morupule Coal Mine uses different equipment which influence production. Therefore, studies on these machines (continuous miners, shuttle cars, feeder breakers, roof bolters and conveyer belts) will show how their combined performance affect production in the mine.

3.4.2 Seam Thickness

Extraction of thicker coal seams results in increased productivity as there is more coal available per square area and the mine machines can manoeuvre more easily within the excavations. Coal seams of smaller thicknesses limit the movement of mine equipment and this results in lower quantity of coal mined and available for processing into finished products resulting in lower production efficiency.

3.4.3 Mine Roof and Floor Conditions

Good to strong roofs result in high levels of production efficiency and is desirable for mining coal. Poor roofs could result in roof failures causing fatalities, damage to equipment and loss of production due to temporary or permanent closure of the affected mining section. This often requires frequent clean-ups, repair of work area, recovery and repair of the damaged equipment. To avoid roof collapse, more man-hours are required for roof support leading to increased production cycles and lower outputs per shift or per day.

Bad floor conditions in an underground mine result in low production output of ore and increased cost of operation. Poor floor conditions may be caused by floor upheaval due to geological conditions or floors that are not cleaned regularly, poor drainage systems or steep gradients (Segopolo, 2015). Ground upheaval causes uneven working surfaces which lead to low haulage efficiency as the speed of equipment is lowered and the cycle time of the system is increased. Thus, measures must be taken to clean and grade the affected areas to make the floor suitable for smooth mining operations. As such more man-hours must be spent on cleaning and grading the floors. Good housekeeping practices is needed to ensure uninterrupted and continuous mining operations. The drainage system has to be set to drain water quickly away from mining areas and the influence of steep gradients on the operation of mine equipment needs to be evaluated.

3.4.4 Annual Production Capacity

The annual production capacity, which is also known as the scale of operation, depends on the number of production input units utilised at the mine. The size and quantity of the working input units affect the production rate. For an underground coal mine that uses continuous miners, the input units include continuous miners, shuttle cars, feeder breakers and conveyor belts. The continuous miners must be matched to the available shuttle cars to ensure smooth and efficient operations. The productivity in underground coal mines differ

from one mine to the other based on the mining methods employed (i.e. whether continuous miners are used in mining the ore or a conventional mining method is used). The conventional mining methods usually result in lower productivity as compared to using continuous miners.

3.4.5 Mine Life

The mine life is the period in which a mine is operational until all operations cease. From the commencement of a mine's operation many developments occur such as opening of new production areas and haulage ways. This development creates longer materials handling routes and transport ways for working personnel. Also, larger working areas need to be monitored and maintained. In addition, the mine equipment deteriorates with time leading to lower equipment efficiencies.

An increase in development openings and production areas result in lower production efficiencies. Plans must be in place to counter any change in production output as the mine expands. In general, when mining operations reach the end of the mine life, productivity slowly reduces.

3.4.6 Quality of Finished Products

The products from the mine can be differentiated as raw coal or clean coal. The raw coal production output is usually higher compared to clean coal production output.

3.4.7 Presence of Water

Accumulation of water in working areas underground lowers production as more production input resources (man-hours) are diverted to drain the water. In most cases, this disturbs or halts production operations until the drainage is complete. As a result, good work practices must be in place for the mining operations to be done continuously without interruptions.

3.4.8 Quantity of Gases Emitted

The concentration of methane and other noxious or explosive gases in the ambient air affects the mining operations as production may have to be stopped to ventilate the area sufficiently to lower the concentrations of the poisonous gases to acceptable levels to ensure the safety and health of workers. Measures in place to control methane accumulations in an underground mine must be constantly monitored and assessed.

3.4.9 Labour Availability and Utilisation

Some of the factors that affect mine productivity are labour utilisation and labour productivity (Aljuhani, 2002; Neingo and Tholana, 2016). High productivity is attained by effective management and use of skilled labour. Tumurchudur *et al.* (2017) list the main factors that negatively affect labour productivity as mine leadership and management qualities, technology and equipment factors, job organisation and planning factors, nature and condition of materials/tools used, safety factors, manpower factors, level of motivation and workplace environment factors such as changing labour. Prevailing government regulations (e. g. health and safety regulations) have also been found by researchers to affect mine productivity.

According to Aljuhani (2002) and Neingo and Tholana (2016) factors influencing labour utilisation and productivity are late work starts, unsanctioned breaks, sanctioned breaks away from work, in mine travels and early quits from work. The non-productive time used by mine personnel has to be investigated to increase productivity. Other factors that affect productivity of workers include the distance to work areas, environmental conditions in working areas, work practices, operator's efficiency and skill level of personnel. The number of personnel working is determined by the scale of the operations and degree of mechanisation.

Anon. (1998) list the factors that affect labour productivity as labour practices, staffing levels, idle time and equipment operating practices. Staffing levels is a description of labour hours worked per total shift hours. Work practices are either operations or processes performed during production (e.g. fuelling equipment during breaks), ensuring that clean-up equipment do not halt production operations, etc.

Occupational health and safety factors also affect labour availability and utilisation. Oxenburg *et al.* (2004) and Katsuro *et al.* (2010) state that personal health and safety is tied to a company's productivity level at all worksites within the operations of the business entity. The working conditions affect the workers in achieving the set targets. Poor working conditions such as use of old and/or wrong equipment may result in workplace injuries leading to low morale of workers and lower productivity. Work injuries and illnesses result in lost production and absenteeism leading to increased losses in man-hours. Personnel

performing strenuous work impact their health negatively and also results in low production output.

Katsuro *et al.* (2010) state that personnel can achieve set targets when the working conditions are suitable such as provision of appropriate work equipment and having effective work practices (e.g. controlling hazards quickly at the sources). The employees also perform better when in good health emotionally and physically thus leading to higher productivity.

3.5 Production Analysis Methods

Production analysis methods are used to evaluate production operation functions. The importance of the assessment is to monitor and improve the production operations in terms of efficiency and effectiveness of the input resources. Production information or data is required to assess the operations and without data the efficiency of the system can neither be determined nor the maximum performance of the system known.

Both quantitative and qualitative methods are used to evaluate production operations. In quantitative analysis methods, statistical techniques are often employed to give an exact description of the current state of production from the collected data on the operations. Statistical evaluations are decision making tools as they lead to the establishment of strategies to monitor and improve the production systems.

3.5.1 Production Process Analysis

Production process analysis is commonly used in production operations to identify connections between different resources to achieve the production targets within a system (Timilsina, 2012). In this context, mining production process refers to a combination of mining operations which may be drilling, blasting, loading, hauling and dumping of ore or waste.

Also included are mine ancillary operations which complement the main production operations. The assessment of production process is in terms of equipment performance, cycle time, labour productivity and production output. The equipment performance evaluations assess the utilisation and availability of equipment. Cycle time analysis

investigates a production shift to measure the productive and unproductive time of the labour and equipment used.

The production process is assessed to identify production constraints to improve the production output volume utilising available resources. Production process flow chart design or subdivision units make it easier to assess the full production system by investigating individual units of the production processes.

3.5.2 Reliability Analysis of Mine Production System

Reliability analysis is the assessment of production inputs and processes to determine consistency of production resources utilisation. If any unit is not working efficiently, this may reduce the efficiency of the entire production system (Kumar and Huang, 1993). The results of the reliability analysis must be at an acceptable level to achieve the defined annual production capacity.

A study by Kumar and Huang (1993) on reliability analysis of mine production systems using sublevel caving method for iron extraction subdivided the production system into three integrated operations which are ore availability and access, the loading process and capacity of the materials handling systems. The factors affecting the three systems were studied and the critical production components identified. Individual performance analysis were performed on the critical components to enhance the production system using a model computation analysis method that was developed. The determinants of production efficiency identified in the study included borehole stability, geotechnical, operator's availability, machine maintainability, power and ventilation.

3.5.3 Overall Equipment Effectiveness

The overall equipment effectiveness (OEE) of a machine is the product of its operational availability, utilisation of the availability, its productivity and quality of operation (Fourie, 2016). OEE is a measurement method used in the manufacturing industry and adapted in the mining industry by Elevli and Elevli (2010). OEE is expressed mathematically by equation (2):

$$OEE = A_v \times U_o \times P \times Q \quad (2)$$

where: A_v = availability of equipment

U_o = utilisation level of available equipment

P = equipment productivity

Q = quality of work performed by equipment

OEE applies to planned production time. However, scheduled time losses are not included. The method combines equipment availability, performance and quality for the evaluation of equipment effectiveness. Availability of unit equipment in a mine determines the machine's operational time, which is the actual time worked by the machine or system (with no unplanned or planned interruptions) as a percent of the total planned production time. Equipment performance indicates the machine speed level and compares it with the normal operational speed set for the mining equipment.

The method evaluates common and important time losses in the unit production processes which are equipment down time losses, time losses due to defects on the equipment and speed losses. The results of the assessment are compared with the benchmark values and if the values obtained are below the benchmark values, the system must be assessed for improvement.

Studies on the effectiveness of equipment usually identify the possible production time losses for mining equipment and classify them as non-scheduled time, scheduled and unscheduled maintenance times, setup and adjustment time, idle time without an operator, loader waiting time, loading time loss, time losses due to job conditions, speed loss and quality loss.

3.5.4 Multi-Linear Regression Analysis

Multiple linear regression analysis is a predictive technique that establishes a correlation between a dependent variable and independent variable(s) in any function where the assumptions of the method are met such as a linear relationship exists between variables and the regression residuals are normally distributed (Anon., 2019b).

The method models a relationship between two or more independent variables and a dependent (response) variable by fitting a linear equation to the observed data (Anon., 2019c). Any value of the independent variable is associated with a certain value of the dependent variable. The method quantifies possible changes that may be affected in a

function by increasing or decreasing an independent variable to achieve a set target by establishing deviations when a unit input changes.

The technique simply correlates function inputs to a function output in production operations. The method applies to a production function where the production output is influenced by productivity factors. A correlation between factors affecting productivity (explanatory variables) and production output (response variable) can be established by multi-linear regression analysis.

Various researchers have shown that machine availability and utilisation affect a mine's production output. So, these factors can be set as independent variables while the machine output or production output will be the dependent variable in the regression analysis. Multi-linear regression analysis can be used to assess the production variables and yield results by comparing all factors that affect the production output (Lanke *et al.*, 2016).

3.5.5 Machine Utilisation, Availability and Capacity Analysis

In general, the performance of any mining equipment depends on the machine's rated capacity, utilisation and availability. A study of equipment utilisation, availability and analysis of contributing factors helps in improving the overall equipment performance. Computation of equipment utilisation and availability as percentages is done by developing proper feedback and defining terms or factors relating to mining equipment. From the production system, data on equipment operating hours and other factors influencing equipment performance is collected to determine the equipment production efficiency and overall efficiency of the production system. Overall equipment efficiency is the product of machine's production efficiency and utilisation (Arputharaj, 2012).

The performance of a production system applied in mining is dependent on the availability and utilisation of mine equipment employed (Arputharaj, 2012). Data on equipment availability and utilisation show the significant influence of equipment (e.g. shuttle car, CM and conveyor belt) on production output. Data required for this analysis include equipment repair, break down, idle and working hours. Graphs of production volume output and equipment availability and utilisation help to establish the relations between production function and changes in equipment use. It means that changes in production output or the rate can be deduced from variations in machine availability and utilisation. The monthly

operating hours lost due to equipment failure or breakdown also indicate the volume of production lost (i.e. lost coal tonnage). It means that the daily equipment production index target, which is a ratio of the actual and planned production of machines, is not met.

For any machine, load moved, rate of production for a shift period and variation of loads from the budgeted daily production capacity can be computed in relation to production performance. Negative differences between the actual and budgeted daily machine capacity index show a decrease in production.

Graphs of the factors that affect availability and utilisation of equipment can be drawn and measures taken to improve the underground mining system performance based on listed factors.

Machine availability and utilisation can be calculated using equations (3) and (4) respectively:

$$\text{Equipment Availability (EQA)} = \frac{\text{MTBM}}{(\text{MTBM} + \text{MDT})} \quad (3)$$

$$\text{Equipment Utilisation (EQU)} = \frac{\text{MFOT}}{\text{MTBM}} \quad (4)$$

where: MTBM = Mean Time Between Proactive Maintenance (e.g. corrective and preventive maintenance)
MDT = Mean Down Time
MFOT = Mean Fully Operational Time

Equation (4) can either be represented as a ratio of actual hours of work per scheduled shift hours or actual hours of work per machine available hours.

Equipment availability (EQA) can also be computed as the ratio of equipment uptime and total work period excluding time lost due to uncontrollable events such as power and water outages as shown in equation (5):

$$\text{EQA} = \left\{\frac{(\text{WT} - \text{UET}) - (\text{UMT} + \text{SMT} + \text{OPT})}{(\text{WT} - \text{UET})}\right\} = \left\{1 - \frac{(\text{UMT} + \text{SMT} + \text{OPT})}{(\text{WT} - \text{UET})}\right\} \quad (5)$$

Equipment utilisation (EQU) can also be computed as the difference between the total work time and equipment downtime and lost time divided by work time as expressed mathematically in equation (6):

$$EQU = \left\{\frac{WT - (UMT + SMT + OPT + CTL + STL + OTD)}{WT}\right\}$$

$$= \left\{1 - \frac{(UMT + SMT + OPT + CTL + STL + OTD)}{WT}\right\} \quad (6)$$

Equipment down time refers to consequential time lost, standby time and operational delay lost time or refers to unscheduled and scheduled maintenance and operational delays time.

Equipment engineering availability (ENA) is the sum of the difference between work time and equipment downtime and uncontrollable events time divided by work time excluding uncontrollable events period (see equation 7):

$$ENA = \left\{\frac{WT - (UET + UMT + SMT)}{(WT - UET)}\right\} \quad (7)$$

where: WT = Work time; UET = Uncontrollable events time
UMT = Unscheduled maintenance time; SMT = Scheduled maintenance
OPT = Operational time losses; CTL = Consequential time loss
STL = Stand by time loss; OTD = Operational delays

Equipment maintenance period and performance changes affect shift operational schedule. Long maintenance hours result in decreased machine availability during a scheduled shift. Machine utilisation may be high during availed hours while total shift production output is low due to prolonged maintenance period or frequent equipment breakdowns in a shift. The equipment mean time to failure and mean time to repair changes affect maintenance performance. The standard times for MCM equipment maintenance are observed for reactive and proactive maintenance. These times give the maintenance reliability period which all maintenance duration must be equal to or less than, i.e. a constant mean time. An evaluation will show the state of maintenance and its impact on production volume output. A correlation between machine maintenance service performance against production rate or production output and time can be established.

3.5.6 Labour Performance Analysis

Labour performance, also known as labour's utilisation and labour's productivity, is evaluated as a ratio of production output to labour input i.e. production output volume divided by the total number of employees or work hours. Labour performance can also be evaluated using labour utilisation and productivity.

Labour utilisation is computed as a percentage of the time the workforce is available for productive work during a scheduled working period while labour productivity is evaluated as the percentage of time that the workforce or individual workers are at the worksite with tools performing productive work (Aljuhani, 2002). Labour utilisation analysis includes investigation of non-productive time by workers, identifying the causes of non-productive time and developing measures to reduce wasted time. The starting and end time, time to travel to and from work areas, and work breaks times (whether planned or unplanned) can be used to express labour lost time. That is the hours lost and the actual hours worked can be computed. As a result, a relation between production volume or rate against labour productivity and time can be established.

3.5.7 Failure Rate Analysis

Failure rate analysis refers to the technique that gives a count of how many times a machine or any asset may fail, or an incident occurred in a certain period due to any identified causes. Data on any asset is statistically analysed to give a ratio of equipment failure counts per operating hour or a specified period. This enables the production planner to know the reliability of a resource or equipment utilised over a certain period of production. This measure can help in identifying and investigating the causes of failure to limit the equipment failures or breakdown experienced and work incidents that halt production. Also, priority areas for improvement can be established and provision of backup equipment made where the mean time to repair and mean time between failure of equipment are known for a certain period in a year.

According to Biały (2017) the analysis of an asset failure frequency of mining equipment or conveyor belt can be investigated using statistical control measures such as the Pareto-Lorenz diagram. The diagram depicts the root causes of the failures experienced or incidence occurring in a clear and simple graphical illustration. The Pareto diagram is based

on the principle which states that 80% of the problems encountered is due to 20% root causes of an effect.

3.5.8 Total Productive Maintenance Strategy (TPMS)

TPMS optimises production by engaging all personnel to lead in work operations to increase the operation's effectiveness and production efficiency. The application strategy minimises or eliminates production failures, unplanned downtimes through process improvement, monitoring of machines and ensuring preventative maintenance.

3.6 Identifying Constraints in Mining Production Process

The methods used to find bottlenecks in a production process are cause-effect techniques, why principles analysis, flow charts or process subdivision unit's analysis and theory of constraints. These methods are applicable in the evaluation of a production process (Timilsina, 2012). Simulation of a production system is another technique used to identify production bottlenecks or constraints. The constraints often lead to failure to achieve the set production targets. Production evaluation methods are applicable in identifying the root causes of a mine production problem.

3.6.1 Cause and Effect Technique

Cause and effect analysis is used to evaluate a production process by identifying the root causes of problems encountered in the mining production operations. The method provides a systematic visualisation of the production bottlenecks or constraints, causes and effects using a schematic diagram (Watson, 2004).

The causes and effects schematic diagram shown in Figure 2 illustrates the correlation between production effect (problem) and the causes of the effects occurring. It also makes it easy for production analysis as those evaluating the production view the entire production system in a simplified form. The analysis establishes areas where data must be collected to correct the effects or a problem (Roy, 1995; Ciocoiu *et al.*, 2010).

Identification of factors causing production inefficiency and their analysis helps in designing effective solutions to increase and sustain production efficiency/capacity. The technique is mainly significant in identifying the root causes of a production effect or problem but fails to measure the magnitude of the root causes. So other analytical methods

must be utilised to measure the degree of the root causes. According to Watson (2004) the techniques fail to correlate the root causes to each other, but it is vital as it can identify the root causes of a production problem.

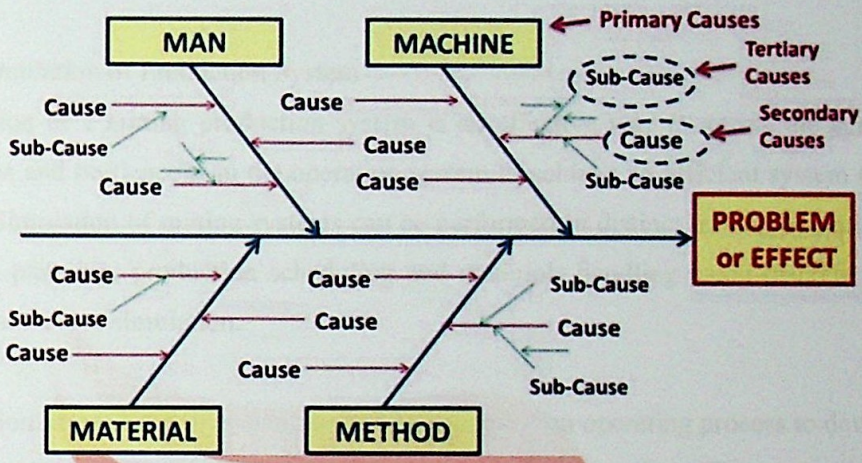


Figure 2 Causes and Effect Diagram (Anon., 2021b)

3.6.2 Flow Chart Design

The design of a flow chart for a mining production operation classifies the mining processes into distinct sub-processes. Individual analysis of these sub-processes reduces the number of factors that contribute to the variation in the process and improves the production output (Parmar and Deshpande, 2014). The time for each process can easily be known and any variations in process operations identified. The failures within the entire system can be easily identified and failure rate analysis can be performed to quantify the causes of failure and correct the operation's performance. Also, the process constraints can be investigated, and corrective measures implemented to achieve the planned production.

3.6.3 Why Principles

Cause effect analysis can be used in combination with the why principle technique. The causes of the effect or problem as depicted in a cause and effect diagram are evaluated to establish the reasons why such a condition occurs. The why principle can be used to assess a production problem or effect by mentioning why it has occurred to identify the root cause of the effect. For effective application of the technique, an accurate statement of the problem must be established and a clear assessment of the most probable root causes in answering the why questions. The identification of probable causes leads to developing effective

measures to correct the production effects (Serrat, 2014). The root causes of production problems must be quantified through data collection and analysis using appropriate statistical and analytical methods. The why principle technique fails to quantify the production problems. Hence, appropriate statistical and analytical methods are used.

3.6.4 Simulation of Production System

Simulation of a mining production system is an effective way to assess the constraints, problems and bottlenecks in the operating system to achieve an efficient system (Mahieu, 2017). Simulation of mining systems can be performed in distinct mining operations such as mine planning, production scheduling and materials handling using discrete event or continuous event simulation.

Simulation assesses the effectiveness and efficiency of an operating process to develop and propose the solutions to problems encountered within the system. The method models a more realistic or accurate production system and data is fed or downloaded into the model to simulate a realistic behaviour of the system. The parameters can be altered to give effective and efficient operations through trials or different combination of production input resources without changing the physical system or interfering in its operations.

3.6.5 Theory of Constraints

Theory of Constraints (ToC) is a production assessment method that is used to improve profitability, efficiency and effectiveness of production operations through the identification of constraints in a production flow process which could be equipment utilisation, number of skilled labour, etc. (Mathu, 2014). In a mining production, ToC can be applied to mining processes such as ore fragmentation, overburden removal, materials handling and mineral processing operations to eliminate the constraints or minimise the effects of the constraints on production. The method is helpful in production scheduling as scheduling problems can be easily fixed.

Elimination of the bottlenecks or constraints on mine operations leads to an increase in production capacity and productivity. The bottlenecks or constraints can be eliminated by following a five-step process namely (Timilsina, 2012):

1) Identification of production constraints.
2) Exploitation of the production constraints.

3) Subordinate non-constraints to exploitation decision.
4) Elevate the constraint.
5) Repeat the above steps.

3.6.6 Relative Importance Index (RII)

RII is a relative measure, weighing the factors affecting a specific function. The study involves participants who work or are experts in a subject field to rate the factors affecting a function according to their perception (Tumurchudur *et al.*, 2017). The measurement indicator establishes the major and minor significant impact factors on a function to focus on developing corrective measures/practices at the current period of study.

3.7 Selection of Statistical and Analytical Methods

Statistical methods refer to a group of linked processes performed in a study to give a meaningful explanation of data and publish/report the findings. The processes include study planning, collection of data and interpretation of data (Ali and Bhaskar, 2016).

Data collection is an integral part for assessing production operations and its analysis gives a direction or guidance to set corrective measures. Poor data collection leads to a low degree of confidence in the statistical analysis which when applied gives inappropriate corrective measures (Ridzuan and Wan Zainon, 2019). If there is no data or shortage of data, production operations cannot be evaluated for any improvement and/or optimisation.

Statistical analysis provides descriptive and inferential statistics. Descriptive statistics show central tendency and spread measures in production figures (data variations). Statistical analysis indicate the direction, change rate and consistency of production output in case of underground coal mine production evaluation. Planning for data analysis includes determination of data type, data period or length, data collection and analysis methods. Data variation signifies changes in production over a period observed in comparison to set production targets. Also, data cleansing is of importance to ensure that inaccurate and incomplete records or figures are removed from the data records before the analysis. Data cleansing leads to a high degree of confidence in statistical analysis.

Statistical and analytical methods result in having values for production output changes per resource use or due to factors that affect production. Factors influencing production can be

quantified e.g. utilisation and efficiency level of either equipment or labour. In simple terms, the analysis shows a casual effect between production variables. This is known as correlation of production variables (Rao, 2007). Also, it establishes the causes and effect relationship between the variables which is known as regression analysis.

The distinction between correlation and regression analysis is that the former establishes direction and degrees of association between variables while the latter expresses a cause and effect relationship between independent factors and a dependent factor. Correlation analysis does not establish the causes and effects (Zaid, 2015).

From the data collected, the impact or magnitude of production variables or factors on production can be significantly measured, corrective measures and effective practices set to improve production. This can be used to solve problems that result in negative production variance. The measures and practices taken guide a mining entity on how to distribute their investment capital or resources to improve production volume output or resource utilisation.

In determining the strength of the correlation, Pearson's coefficient is computed. Pearson's correlation coefficient (r) is a measure of the strength of the association between the two variables. The correlation value of Pearson's coefficient ranges from -1 to 1 (Zaid, 2015). Pearson's coefficient between various production factors is calculated to show the direction and strengths of the relationships. Strength of association establishes the degree of relationship between the parameters i.e. whether there is strong, weak, moderate, direct or indirect correlation or no correlation at all. The values of Pearson's correlation coefficients show both direction and strength of association. A positive value shows a positive direction and direct relationship between variables while a negative value shows a negative correlation and an indirect relationship between the variables.

Coefficient values ranging from -1 to 0 signify an indirect or negative correlation while values from 0 to 1 signify direct/positive correlations. Strong direct or indirect correlation means the Pearson's coefficient value is very close to or equal to 1 or -1. Meaning a change on one variable shows a more significant change on the other variable. A correlation value of zero means no correlation and all coefficient values very close to zero mean very weak correlations. A moderate correlation is signified by a mid-value or values close to mid-value in Pearson's coefficient scale either for direct or indirect relationship.

To quantify the changes in independent variables by a unit or influence on production output, inferential statistics using regression analysis is performed to determine the changes in production, in terms of volume, caused by an independent variable's performance. The method follows steps which determine the direction and degree of association between variables, plotting trendlines of data and computing the percentage changes between independent variables and dependent variables.

SPSS Statistical package has a regression data analysis function. A square of Pearson's coefficient gives a determination coefficient value $(r_{yx})^2$ in regression analysis, which indicates the percent change of production performance by the observed variable. Regression analysis can be performed as either simple regression or multi-regression. Simple regression analysis deduces the value of the impact of individual factors on the overall production performance. Multi-regression analysis deduces the value of grouped independent factors on the overall production. Equations (8) and (9) are the functions for simple and multi-regression analyses respectively:

$$Y = B_0 + \beta_1 X_1 + \varepsilon_1 \quad (8)$$

$$Y = B_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_1 \quad (9)$$

where: Y = Dependent variable

B_0 = Independent variable intercept

β_1, β_2 and β_3 = Regression variable coefficients

ε_1 = Error term

X_1, X_2 and X_3 = Independent variables

Regression analysis is performed when certain assumptions are met. Overlooking statistical tests for such assumptions results in over or under-estimating their statistical significance, incorrect effect sizes and/or errors (Osborne and Waters, 2003).

Statistical tests must be applied before performing regression analysis to assess the following assumptions (Osborne and Waters, 2003):

1. Linearity: Variables must have a linear relationship.
2. Reliability of measurement: No error in measurement.

3. Normality: Error must be normally distributed.
4. Homoscedasticity: Error values (also known as residuals) for independent variables must be equal (same variance). Residuals/error values refer to a variation between observed/measured and predicted value of a dependent variable.
5. No multicollinearity: Independent variables must not be highly correlated. If variables are highly correlated, the analysis outcome will result in variance results inconsistency between independent variables.
6. No autocorrection: Residuals must be independent of one another.

When assumptions are met, there is a high degree of confidence in the results. MATLAB and other statistical software's perform regression functions for linear and nonlinear regression.

Figure 3 shows the detailed methodology that was used in the study at MCM.

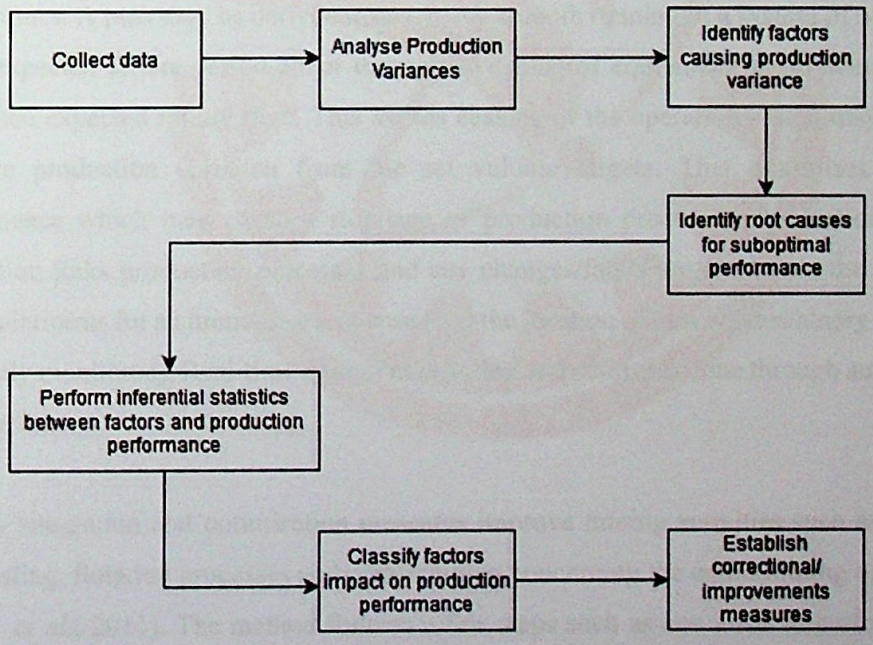


Figure 3 Flow Chart of Study at MCM

3.8 Mining Productivity Growth Benefits

Mining productivity growth refers to improving mining production performance utilising available input resources (e.g. equipment and labour). In maximising productivity, these

resources produce additional outputs without even increasing their volume or operation time by using them effectively and efficiently. As a result, the efficiency or performance of the mining process and operation is increased. Mining systems are integrated and any operation/process improvement is performed to ensure that the entire system is optimised. Also, productivity growth in mining brings better working conditions and labour efficiency is increased and the mining entity earns higher financial returns (Anon., 2014).

3.9 Productivity Improvement Technologies in Mining

Technological advancements maximise production as it offers computation of large data using advanced statistics, integration of mine processes, real-time production monitoring, predictive models for equipment failure and ground monitoring systems (Durrant-Whyte *et al.*, 2015).

Failure prediction models forecast system/equipment reliability period before failure. Failure predictive systems can be used by mines in their proactive equipment maintenance programmes. A plan may be derived to ensure the smooth running of a system of operations at the expected failure period either through switching of equipment or servicing system before the expected failure time. This avoids ceasing of the operation which may cause a negative production variation from the set volume targets. This minimises reactive maintenance which may cause a stoppage of production processes. Production system integration links production processes and any changes/faults are shown on the system's digital platforms for an immediate response (e.g. the location of moving machinery is shown and easily monitored). Real-time system monitoring and control is done through automation of operations.

Process integration and optimisation measures improve mining activities such as drilling and blasting, flotation processes and comminution concerning the entire mining operations (Valery *et al.*, 2011). The method follows a few steps such as site visits to perform main mining process audits, ground characterisation and measurement to develop a mine's specific model to improve the entire mining operation. The model is tested before implementation through simulations to obtain increased production output for the entire production. Mining productivity growth technologies lead to cost reduction in the operations, increased production performance and improved overall production efficiency.

CHAPTER 4

DATA COLLECTION AND ANALYSIS

4 INTRODUCTION

This chapter contains the data collection methodology, data analysis and discussions on the study findings.

4.1 Data Collection

Data was collected mostly from mine records and reports (primary data sources). Quantitative and qualitative techniques were used in analysing the data in this Chapter.

4.1.1 Field Work

Several trips were undertaken to MCM for familiarisation with the mine's production operations and processes. Through mine visits, production scale was established i.e. the planned shift output volumes, duration of shifts, number of shifts in a day, number and type of equipment used in the mine, the rated daily capacities of the machines and number of underground personnel per shift or section.

4.1.2 Viewing and Retrieving of Mine Records

Primary data recorded by mine officials at production sections was collected and used to assess the operational performance of the mine. Data obtained during the study included planned and achieved production outputs, machine availability reports, equipment maintenance and production operational reports. The records include machine downtimes, idle times and fully operational hours.

4.1.3 Consultations and Interviews

Discussions with mine officials were held to get first-hand information about the mining operations and processes. Through consultations, production parameters and mine production key performance indicators were established. The mining teams typically record the production output and all delays in the operations during the shifts in logbooks and these are kept as part of the mine's operational reports.

4.2 Data Analysis

Statistical methods were used to analyse the mine's operational data to determine yearly and shift production variances and the impact of resources used on the mine's productivity. In the data analysis, production variants and cause-effect of production changes were identified.

4.2.1 Production Data Variance

Figure 4 shows the yearly actual and planned production outputs from 2015 to 2020. It shows that the planned production targets were never met in the years 2015, 2016, 2019 and 2020 but were met in only in 2017 and 2018. The descriptive data for the actual production performance (in tonnage) is summarised in Table 1. The lowest production of 1,827,982 t was in 2019 while the highest production of 2,48,2311.61 t was achieved in 2018. Production was fluctuating from 2015 to 2020. The production targets for the observed period varied from 1,913,830.04 t in 2017 to 2,766,955 t in 2015. Production targets varied through the years. The mean production over the period from 2015 to 2020 was 2,067,320.80 t.

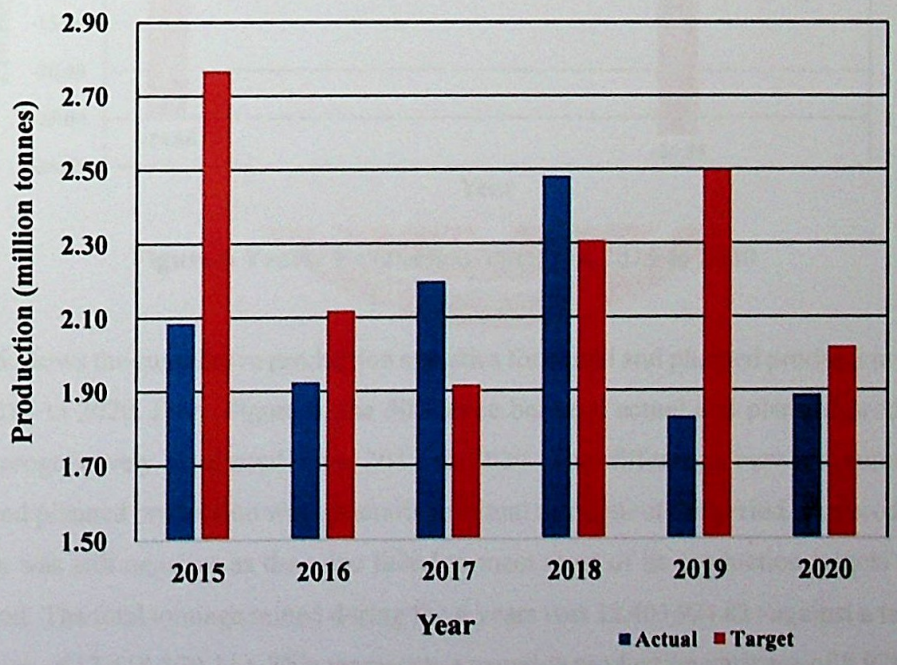


Figure 4 Actual and Planned Production Performance from 2015 to 2020

Table 1 Descriptive Statistic for Production Performance

Feature	Mean (t)	Minimum (t)	Maximum (t)	Range (t)	Standard Deviation (t)	Sum (t)
Production Output	2,067,320.80	1,827,982	2,482,311.61	654,329.61	244,715.45	12,403,924.82

Figure 5 shows the percent variances between actual and targeted production from 2015 to 2020. From Figure 5, the difference between actual and targeted production values varied from -26.85% in 2019 to 14.81% in 2017.

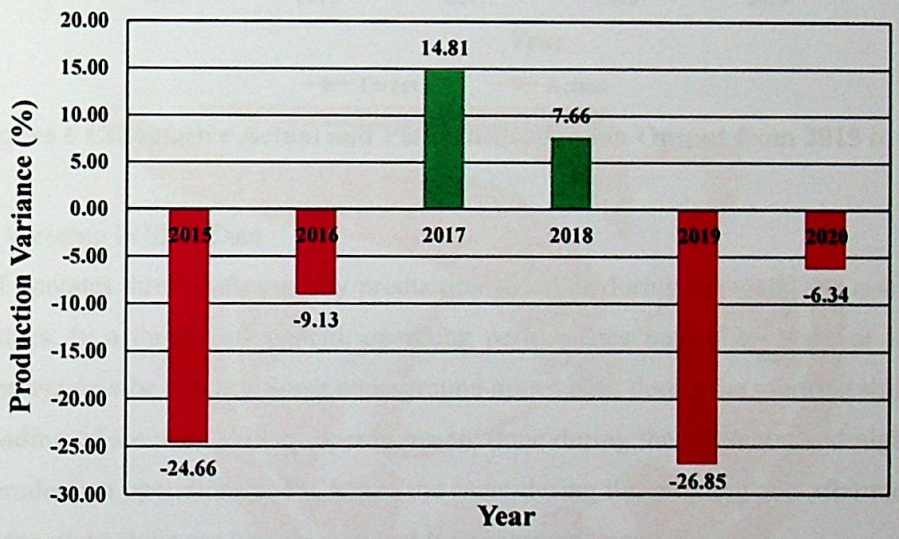


Figure 5 Yearly Production Variance 2015 to 2020

Figure 6 shows the cumulative production statistics for actual and planned production values from 2015 to 2020. From Figure 6, the difference between actual and planned production values progressively fluctuated from 2015 to 2020. The difference between cumulative actual and planned production was generally minimal throughout the period. But production variance was still negative as the mine failed to meet most of its production targets during the period. The total tonnage mined during the 6 years was 12,403,924.82 t against a targeted production of 13,618,379.31 t. This represents a negative production variance of 8.92% over the six years. The production targets were not achieved during the period even though production operations were carried out in all the 3 shifts including night shifts which are usually reserved for maintenance services.

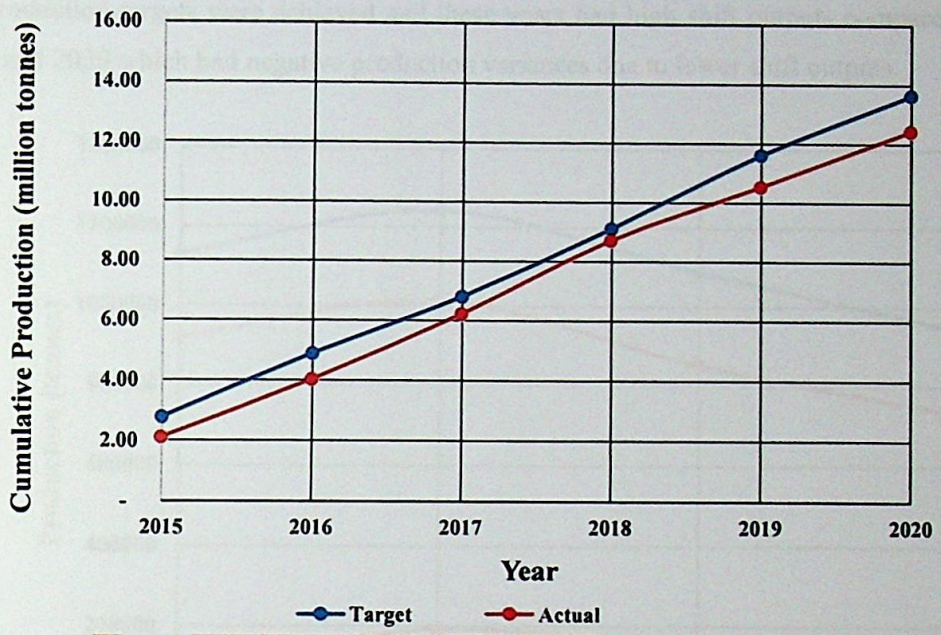


Figure 6 Cumulative Actual and Planned Production Output from 2015 to 2020

4.2.2 Variance in Shift Data

MCM operates three-shifts per day production schedule during the week and one shift on Saturdays. In a three-shift system, operating performance may either vary or the work assignment may be distinct. Some underground mines blast during the morning shifts while the loading of ore and ancillary operations are done during the afternoon and night shifts. The production operations at MCM are the same during the morning and afternoon shifts while the night shifts are usually reserved for equipment maintenance.

Figure 7 shows the total yearly production during the morning, afternoon and night shifts (it includes data from the weekend shifts) from 2017 to 2020. The daily target production per shift varied monthly and yearly over the period of study. It can be observed that higher production outputs were generally achieved during the morning shifts than in the afternoon and night shifts.

Night shifts are usually reserved for the maintenance of underground equipment but occasionally some minimal production is done during the night shifts to complement the production from morning and afternoon shifts so as to achieve the production target during weekdays as during the weekend there is only one day shift on Saturday. In 2017 and 2018

the production targets were achieved and these years had high shift outputs compared to 2019 and 2020 which had negative production variances due to lower shift outputs.

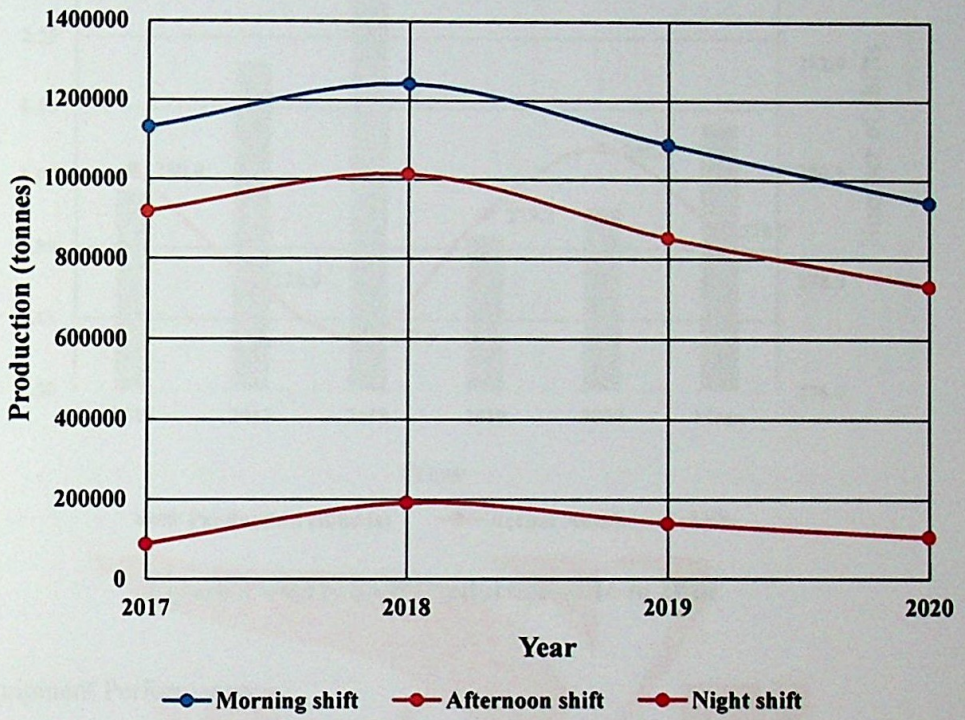


Figure 7 Overall Shift Performance from 2017 to 2020

Figure 8 shows the yearly production during the 3 shifts and the number of shifts operated per year. It is noted that the yearly shift counts varied over the period from 277 shifts in 2018 to 280.4 shifts in 2020. Though the number of shifts per year increased from 2018 to 2020 the production targets were not met in those years. The highest production output was achieved only in 2018 though it had the lowest number of shifts (see Figure 8).

There were an average 278.9 shifts per year over the 6 years. The highest number of production shifts were recorded in 2020 but the actual production was lower than the other years except for 2019. In 2017 and 2018, the planned production was achieved though these years had the lowest shift counts.

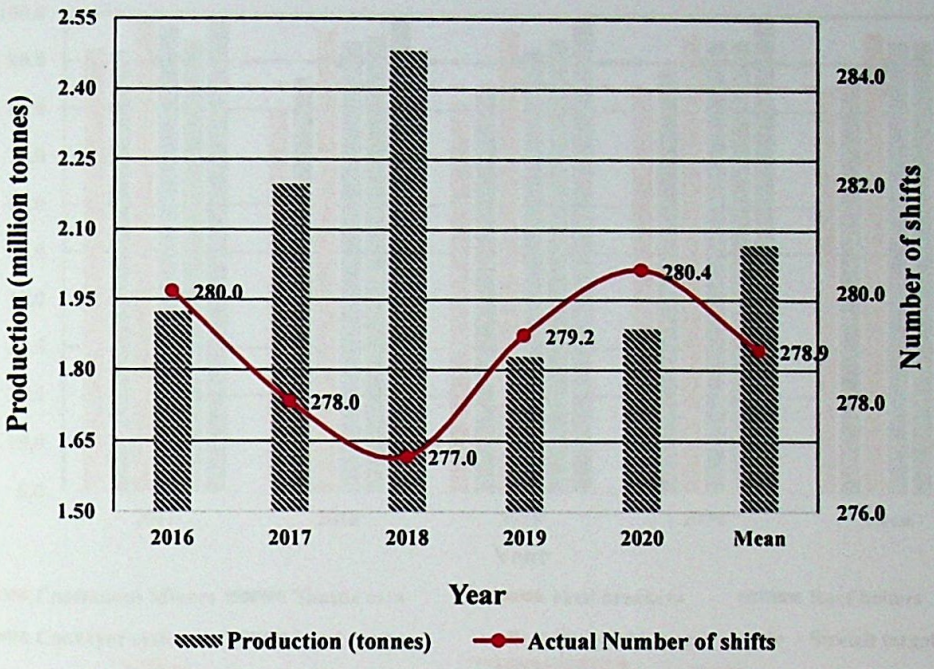


Figure 8 Yearly Shift Production 2016 to 2020

4.2.3 Equipment Performance

The performance of critical underground production equipment can be assessed using equipment availability (EQA), engineering availability (ENA) and equipment utilisation (EQU). As already mentioned, MCM has four operating sections and each section has one CM, a roof bolter and feeder breaker, a load centre, two Load Haul Dump (LHD) machines and three shuttle cars. Assessment of the production equipment was done on the 4 CMs, 12 shuttle cars, 4 roof bolters, 4 feeder breakers, 4 section conveyor belts and 4 loading centres.

Figure 9 shows the yearly equipment availabilities from 2017 to 2020 while Table 2 shows the details of the equipment availabilities. The EQA threshold and stretch targets at MCM are 85.0% and 90.0% respectively for all equipment.

From Figure 9, the availabilities of the shuttle cars varied from 84.0% to 92.0%. The threshold target availabilities of the shuttle cars were achieved in 2017, 2018 and 2020. The availabilities of shuttle cars were below the targets in 2019. The availabilities of continuous miners during the period varied from 79.5% to 92.2%. The continuous miners achieved the threshold target only in 2017.

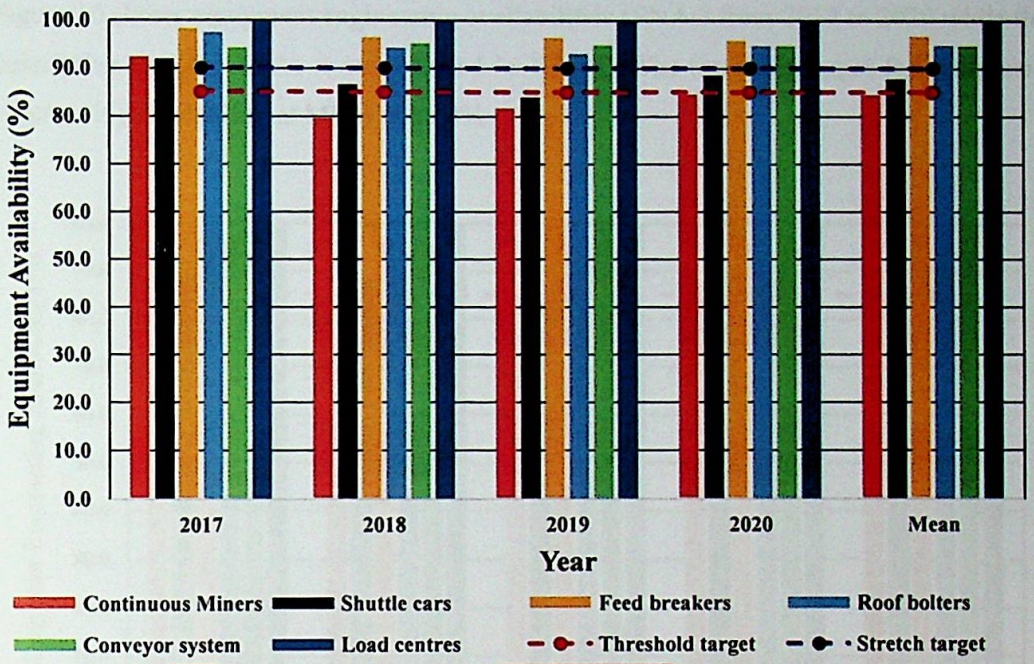


Figure 9 Equipment Availability (EQA) from 2017 to 2020

Table 2 Descriptive Data on Equipment Availabilities

Feature	Mean (%)	Minimum (%)	Maximum (%)	Standard Deviation (%)	Variance (%)	Range (%)
CMs	84.48	79.5	92.2	5.54	30.71	12.7
Shuttle cars	87.83	84.0	92.0	3.36	11.31	8.0
Roof bolters	94.88	93.1	97.4	1.82	3.30	4.3
Feed breakers	96.60	95.7	98.1	1.04	1.08	2.4
Conveyor systems	94.75	94.2	95.2	0.42	0.18	1.0
Load centres	99.85	99.7	99.9	0.10	0.01	0.2

Feeder breakers, conveyor belt systems, load centres and roof bolters achieved their threshold and stretch targets over the period from 2017 to 2020 and their average values were above 94.0% (see Figure 9). Over the same period, the average values for CMs and shuttle cars were below 88.0%. Thus, the equipment with low availabilities were CMs and shuttle cars.

Figure 10 shows equipment engineering availabilities (ENAs) from 2017 to 2020 while the descriptive data for ENAs is summarised in Table 3. The threshold target for equipment engineering availability at MCM is 85.0%.

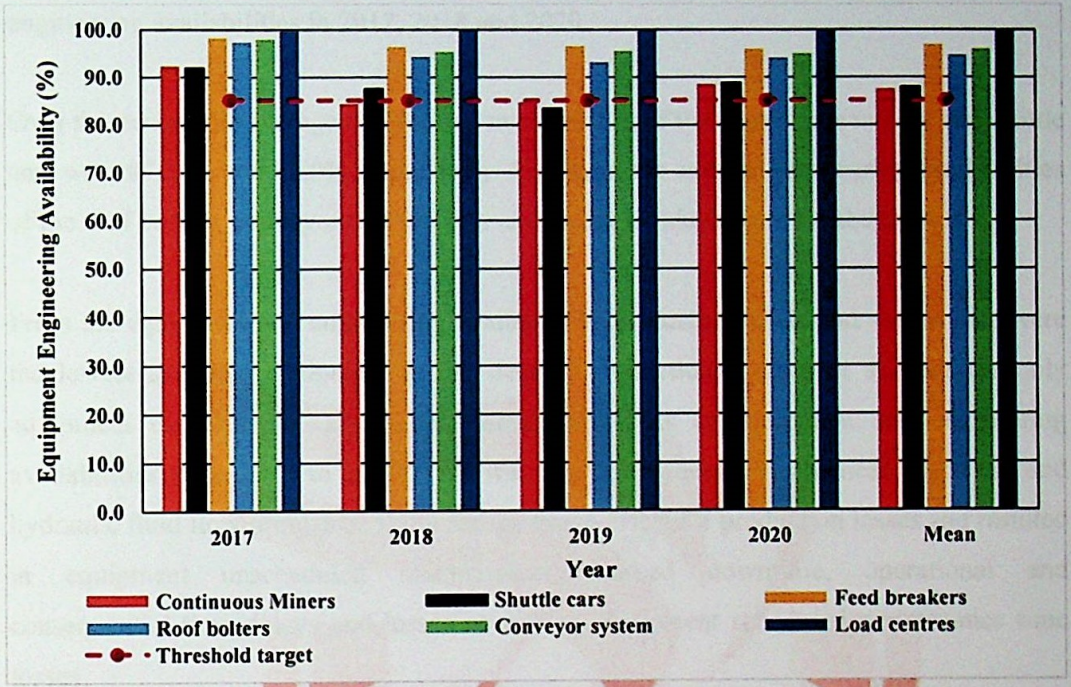


Figure 10 Equipment Engineering Availability from 2017 to 2020

Table 3 Summary of Equipment Engineering Availabilities

Feature	Mean (%)	Minimum (%)	Maximum (%)	Standard Deviation (%)	Variance (%)	Range (%)
CMs	87.34	84.3	92.2	3.72	13.83	7.9
Shuttle cars	88.00	83.5	92,0	3.51	12.33	8.5
Roof bolters	94.75	93.2	97.4	1.83	3.35	4.2
Feed breakers	96.70	95.9	98.1	0.97	0.93	2.2
Conveyor Systems	96.00	95.1	98.0	1.34	1.80	2.9
Load Centres	99.83	99.7	99.9	0.10	0.01	0.2

The feeder breakers, conveyor belt systems, roof bolters and load centres achieved their set yearly threshold targets during the period and recorded equipment engineering availabilities

> 93.0% during the period. The engineering availabilities of the CMs ranged from 84.3% to 92.2% during the period. Thus, the engineering availabilities of the CMs exceeded the threshold target only in 2017 and 2020. The engineering availabilities of shuttle cars varied from 83.5% to 92.0% meaning that the shuttle cars exceeded the threshold targets of their engineering availabilities in 2017, 2018 and 2020.

Over the period, the average engineering availabilities of the continuous miners and shuttle cars were 87.34% and 88.0% respectively. However, the average engineering availabilities of the roof bolters, conveyor belt systems and feeder breakers were all above 94.0%.

From the equipment and engineering availabilities evaluation, CMs and shuttle cars were the lowest available equipment in the fleet of production equipment and are the only equipment that did not achieve the threshold targets of equipment and engineering availabilities from 2017 to 2020. This was due to numerous mechanical, electrical and hydraulic fluid flow problems. These are the cause-effect for production losses and resulted in equipment unscheduled maintenance/unplanned downtime, operational and consequential time delays and losses as well as equipment scheduled maintenance time losses.

The CMs experienced problems such as cutter motor trips, thermal overloads, water circulation failure, faulty methane sensors, draining out of oil which is mixed with water, defective aerial lights, voltage circuit breakers, cutter shear downtimes, loose signals frequently, broken conveyor cylinders and chains, burst hydraulic hoses and failing to engage the pump.

The shuttle cars had problems such as defective aerial lights due to voltage open circuit breaker, faulty pump relays which fail to engage the pumps, tripping when the fan is engaged, defective valve banks, conveyor chain jams and faulty variable frequency drives, broken steering cylinders, hard steering and driveshaft bends, broken steering knuckles and failure to turn, uninstalled canopies and worn out tyres, broken prop shaft bolts, defective wheel units and machine re-hosing, faulty door interlock switches, defective propeller shafts, defective take-up shafts and binding brakes, broken conveyor chain and broken tensioning bolts.

Figures 11 and 12 show the yearly production versus the equipment availabilities of the CMs and shuttle cars from 2017 to 2020. Production output increased from 2017 to 2018 though both the equipment and engineering availabilities of the CMs and shuttle cars declined over the period. There was a drop in production in 2019. Production increased from 2019 to 2020 together with the equipment and engineering availabilities of both the CMs and shuttle cars. There were varying correlations between the equipment and engineering availabilities of the CMs and shuttle cars with production performance. Performance improvement of these variables could lead to achieving optimum production performance.

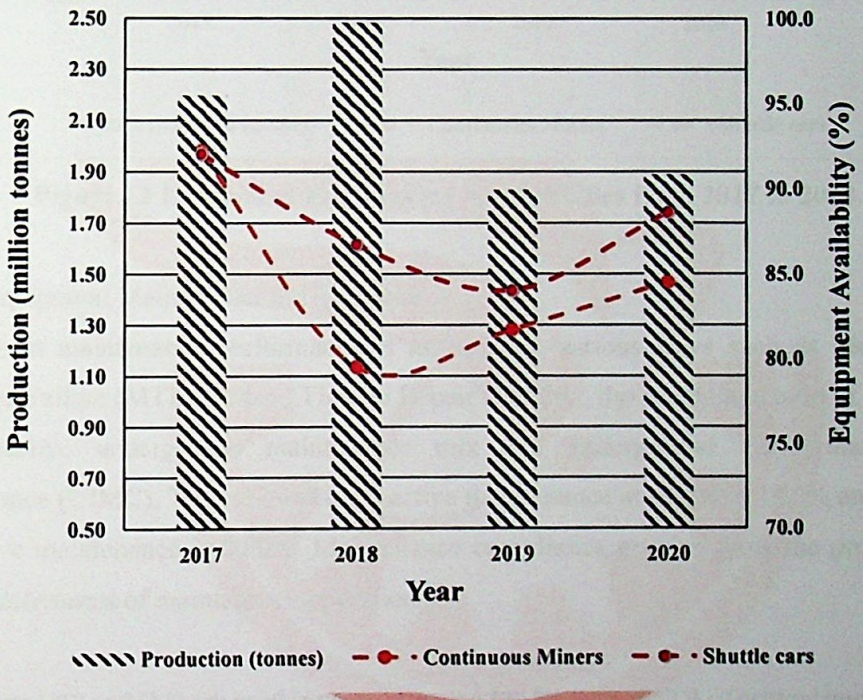


Figure 11 Equipment Availabilities from 2017 to 2020

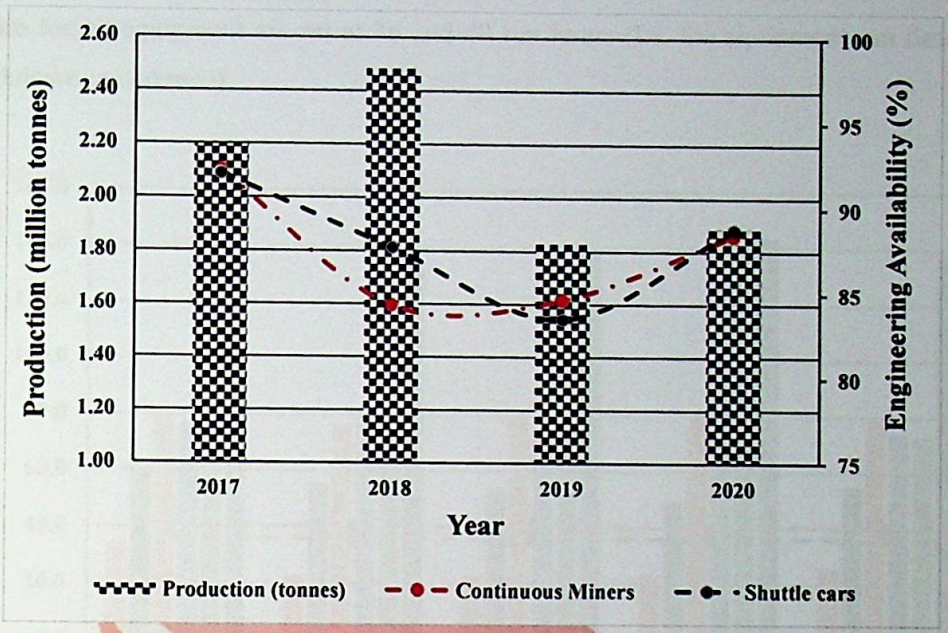


Figure 12 Equipment Engineering Availabilities from 2017 to 2020

4.2.4 Equipment Maintenance Performance

Equipment maintenance performance is assessed in various ways such as Mean Time Between Failure (MTBF), Mean Time to Repair (MTTR), the percentage ratio of proactive and reactive underground maintenance mix and underground inbye maintenance compliance (UIMC). The set level for reactive maintenance at MCM is 20.0% and that for proactive maintenance is 80.0%. Maintenance compliance metrics show the productivity and effectiveness of maintenance operations.

Equations (10) and (11) are used in computing the MTBF and MTTR of critical underground production equipment:

$$\text{MTBF} = \frac{\text{Total run hours}}{\text{Number of breakdown occurrences}} \tag{10}$$

$$\text{MTTR} = \frac{\text{Total downtime hours}}{\text{Number of breakdown occurrences}} \tag{11}$$

Figure 13 shows the calculated yearly Mean Time Between Failure (MTBF) of the equipment from 2017 to 2020. The threshold and stretch targets for mean time between

failure for all equipment are set at 36 and 40 run hours (i.e. the equipment run time per breakdown occurrence).

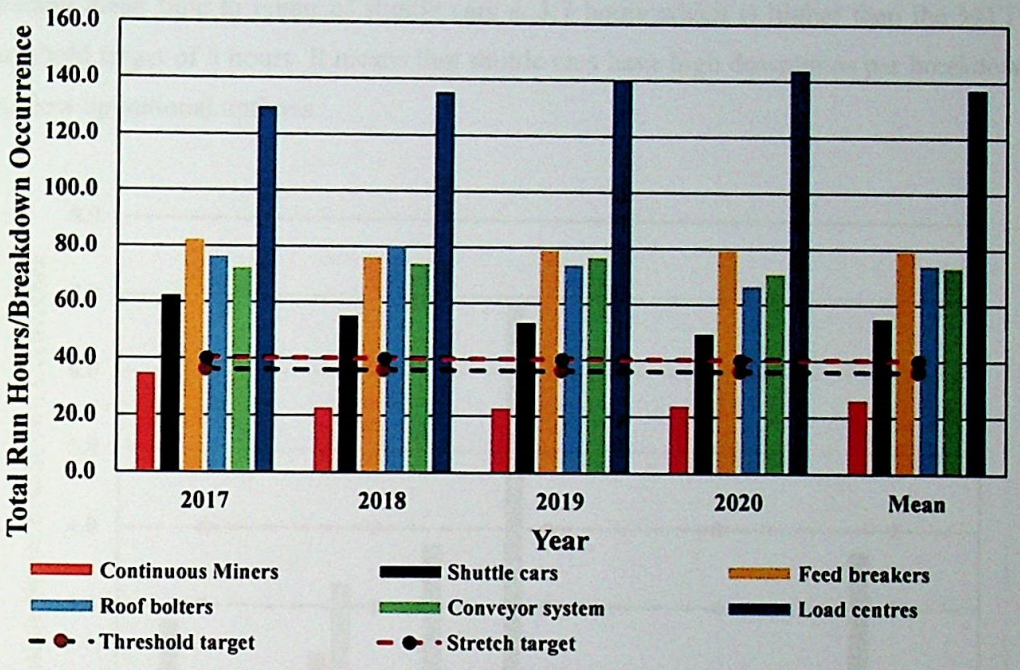


Figure 13 Equipment Mean Time Between Failures from 2017 to 2020

From Figure 13, the mean time between failures of feeder breakers, roof bolters, load centres, conveyor belt systems and shuttle cars were all consistently above the set threshold and stretch targets over the period. The run hours per breakdown of load centres were much higher (averaging 137.2 hours) than the stretch targets (40 run hours per breakdown occurrences). The CMs were the only equipment with low actual run hours before breakdown. This means that the CMs break down more frequently than the other types of machinery. This is evidenced by the low run hours which were persistently less than the set threshold target from 2017 to 2020.

The mean time between failure of CMs ranged from 22.3 hr to 34.4 hr. The average MTBF of CMs over the period was 25.7 running hours per break down. CMs have low MTBF values due to their frequent breakdowns. The shuttle cars and feeder breakers had low MTBF values of 49.4 hr. and 66.5 hr respectively. However, the MTBF values of the other equipment were $\geq$ 48 hours (two days).

Figure 14 shows the yearly equipment Mean Time to Repair (MTTR) values for shuttle cars, CMs, feeder breakers, load centres and roof bolters from 2017 to 2020. The mean time to repair threshold and stretch targets are set at 3 hr and 4 hr respectively. From Figure 14, the average mean time to repair of shuttle cars is 3.7 hours which is higher than the MTTR threshold target of 3 hours. It means that shuttle cars have high downtimes per breakdown and low operational uptimes.

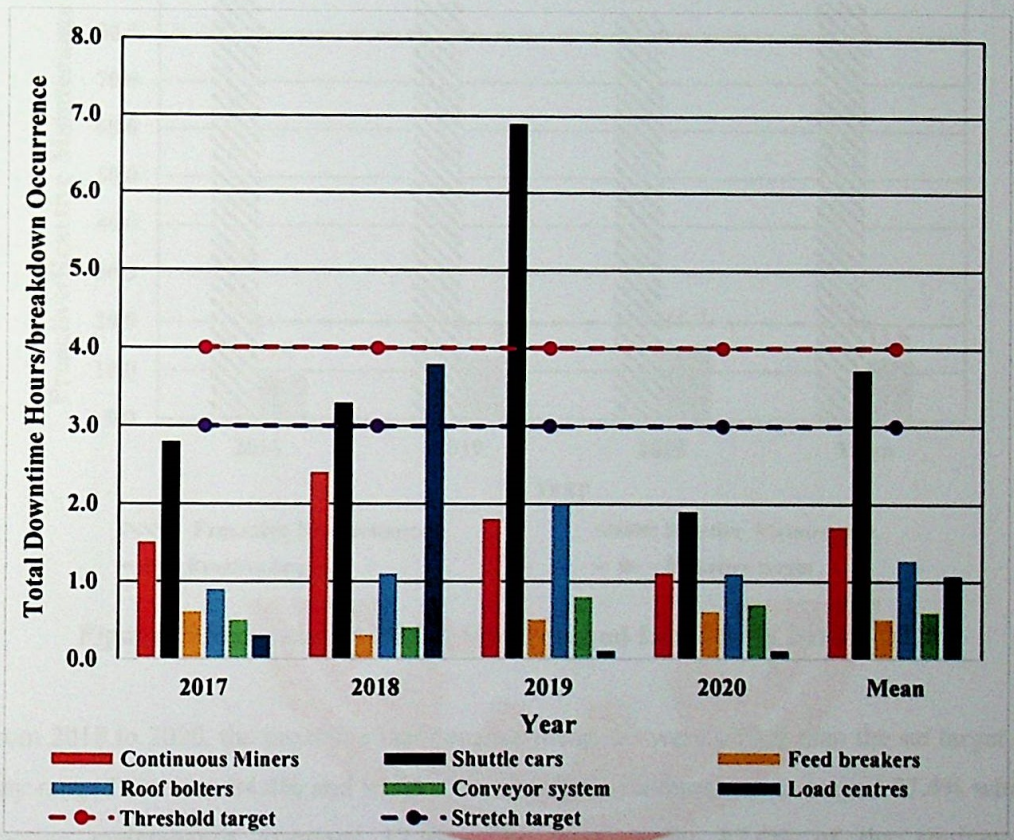


Figure 14 Equipment Mean Time to Repair from 2017 to 2020

The average downtimes per breakdown occurrences for CMs, feeder breakers, load centres, conveyor belts and roof bolters are 1.7 hr, 0.5 hr, 1.1 hr, 0.6 hr and 1.3 hr respectively. Feeder breakers, CMs, conveyor belts, roof bolters and load centres have values which are less than the set MTTR threshold target. Such equipment can be serviced in less than 3 hours and have high equipment and engineering availabilities except for CMs. Also shuttle cars had low EQA and ENA. This appears to account for the monthly and yearly negative production outputs at the mine over the years.

Maintenance mix is a measure of the effectiveness of the established maintenance programme using proactive and reactive maintenance to have high equipment MTBF and lower equipment MTTR values (i.e. to maximise equipment uptime). Figure 15 shows the maintenance mix of underground inbye assets from 2018 to 2020.

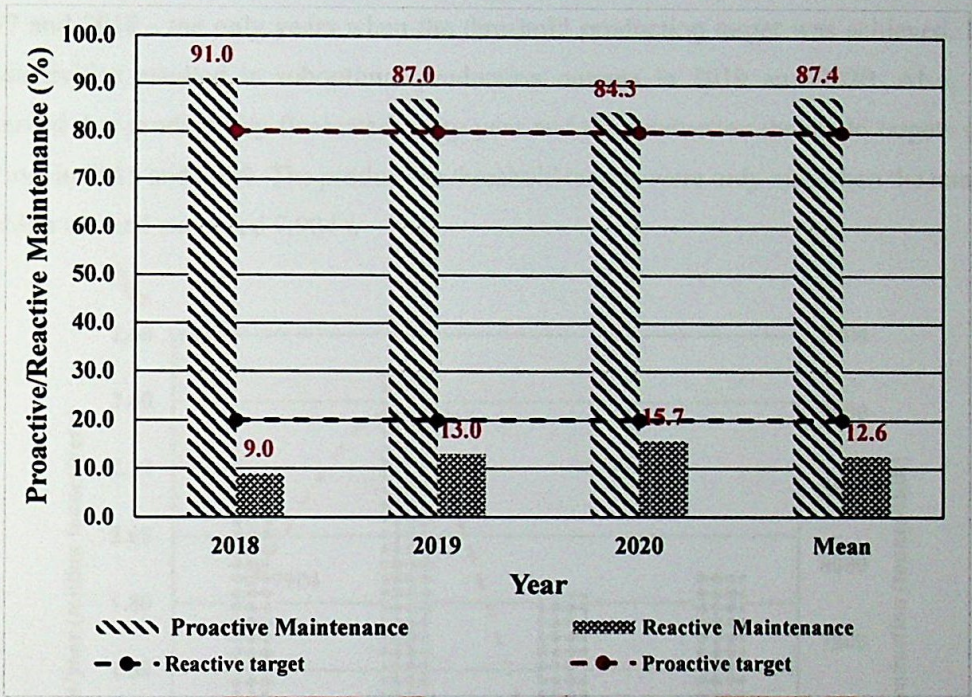


Figure 15 Maintenance Mix at Underground Inbye from 2018 to 2020

From 2018 to 2020, the proactive maintenance measures were higher than the set target as they ranged between 84.4% and 91.0%. The proactive maintenance averaged 87.4% while reactive maintenance averaged 12.6%. This means that 87.4% of the equipment failures/breakdowns were prevented before failure by performing preventative measures. The proactive maintenance value for 2018 was 94.0%. As a result, the mine had higher production performance in 2018 than in the other years. From 2018 to 2020 the actual reactive maintenance performance ranged from 9.0% to 15.7%. There were high reactive maintenance values of 13.0% and 15.7% but low production performances in 2019 and 2020 respectively.

4.2.5 Yearly Production Comparison

Annual production comparisons were done by computing the ratio of production to total shifts worked in each year. Figure 16 shows the production per year and overall production per shift from 2017 to 2020. The production per shift from 2017 to 2020 varied from 6,547 t to 8,961 t. It can be seen that higher productivities resulted in higher production outputs in 2017 and 2018 - the only years when the threshold production target was achieved. Low productivities resulted in suboptimal production outputs in 2019 and 2020. Also, it is observed that productivity fluctuated every year and the production threshold targets were not met in 2019 and 2020. The production threshold targets were only met when the number of shifts worked exceeded 7,904 t.

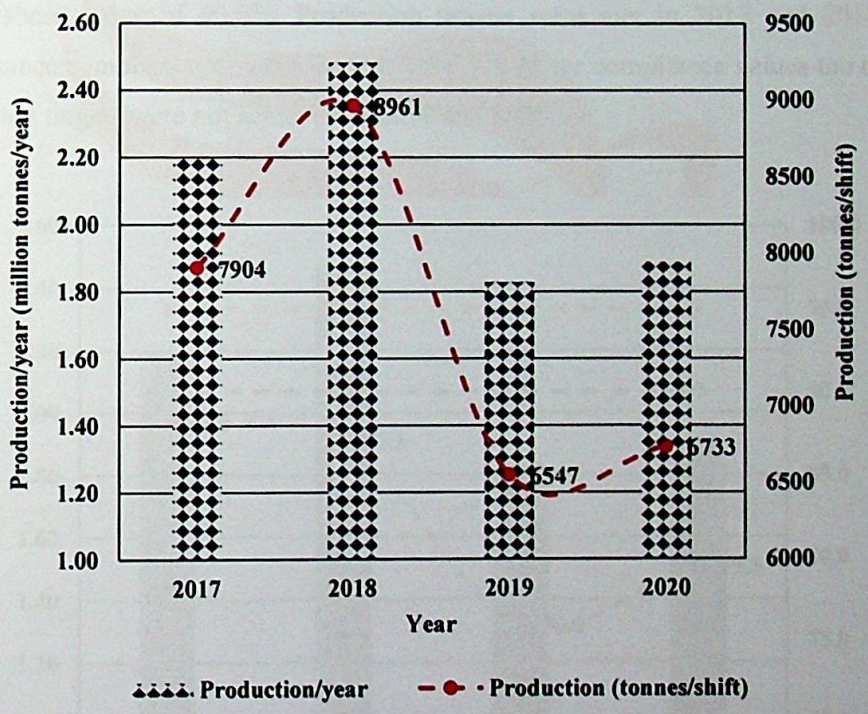


Figure 16 Production Performance from 2017 to 2020

From 2017 to 2020, the higher production outputs were in 2017 and 2018. This can be attributed to several factors such as high equipment and engineering availabilities, high proactive maintenance, low reactive maintenance and enhanced underground inbye maintenance compliance performance. Also from Figure 16, the trend in production output from 2017 to 2020 indicates that declining production outputs per shift or year were likely due to high reactive maintenance/declining proactive maintenance, low equipment and

engineering availabilities of CMs and shuttle cars (as evidenced in the 2019 production data).

Figure 17 shows the maintenance metric for scheduled underground inbye maintenance compliance (UIMC) from 2017 to 2020. The threshold target is 90.0%. The achieved compliance over the period were less than the threshold target of 90.0%. The least achieved compliance of 76.0% was in 2019 while the highest achieved maintenance compliance value of 88.2% was in 2017. The maintenance variance between the years can be said to be high. From 2017 to 2019 there was a decline in maintenance compliance by about 12.5%. Many issued maintenance work orders/services were not completed. There was a slight increase of 3.5% in completed maintenance works from 2019 to 2020 but still this lagged behind the set threshold target of 90.0%. Production targets were met in 2017 and 2018 as the maintenance compliance values were ≥ 87.1%. For lower compliance values the threshold production targets were not achieved in 2019 and 2020.

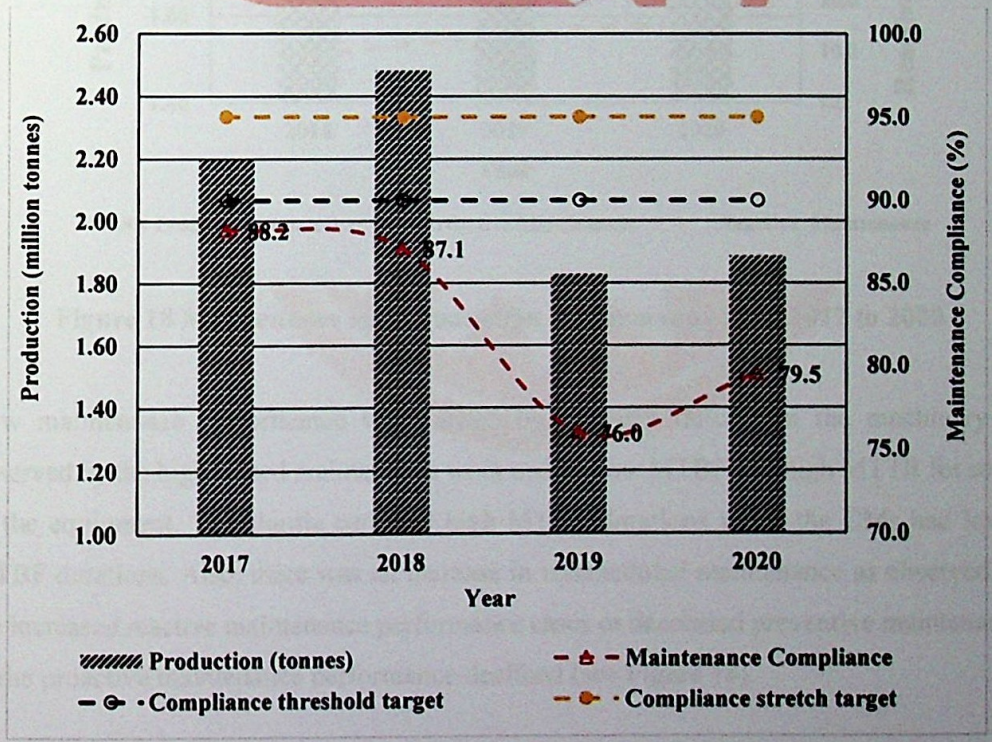


Figure 17 Scheduled Maintenance Compliance Underground Inbye from 2017 to 2020

Figure 18 shows the maintenance mix and production output at MCM from 2018 to 2020. There were high proactive maintenance cases (≥ 90%) and low reactive maintenance cases

(≤ 15.7%) recorded over the period. In cases where the proactive maintenance values exceeded 90.0% as in 2018, the threshold production was achieved. Where there were lower proactive maintenance values as in 2019 and 2020, the production targets were not met. Thus low proactive or increased reactive maintenance values resulted in the mine's threshold production targets not being met in 2019 and 2020.

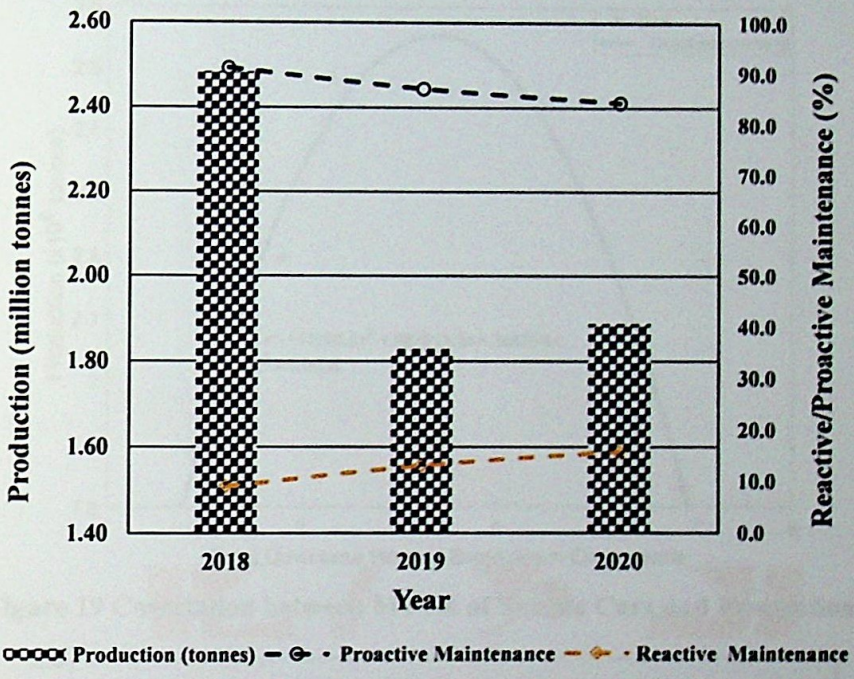


Figure 18 Maintenance and Production Performance from 2017 to 2020

Low maintenance performance was caused by frequent failures in the machinery as observed by the high issued maintenance work orders, low MTBF and high MTTR for some of the equipment. The shuttle cars had high MTTR durations while the CMs had lower MTBF durations. Also, there was an increase in unscheduled maintenance as observed by the increased reactive maintenance performance cases or decreased preventive maintenance as the proactive maintenance performance declined (see Figure 18).

4.2.6 Correlation and Regression Analysis

Correlation analysis was performed on factors that affect production performance from 2017 to 2020 using MATLAB. Few data points were used as the available data was for a period

of three and fourth years. The 2nd-degree polynomial regression was found to be a better fit for most of the data points. A higher polynomial model was found to overfit the data points.

Figures 19 to 22 show the correlation between the performance of shuttle cars and production output. The correlation model equations are shown in all the figures including the R-squared values known as the determination coefficient/explained variation.

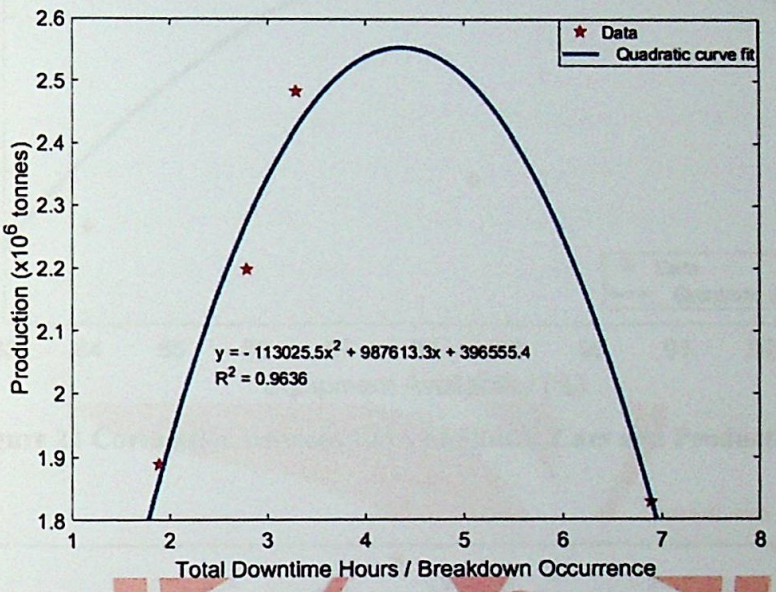


Figure 19 Correlation between MTTR of Shuttle Cars and Production

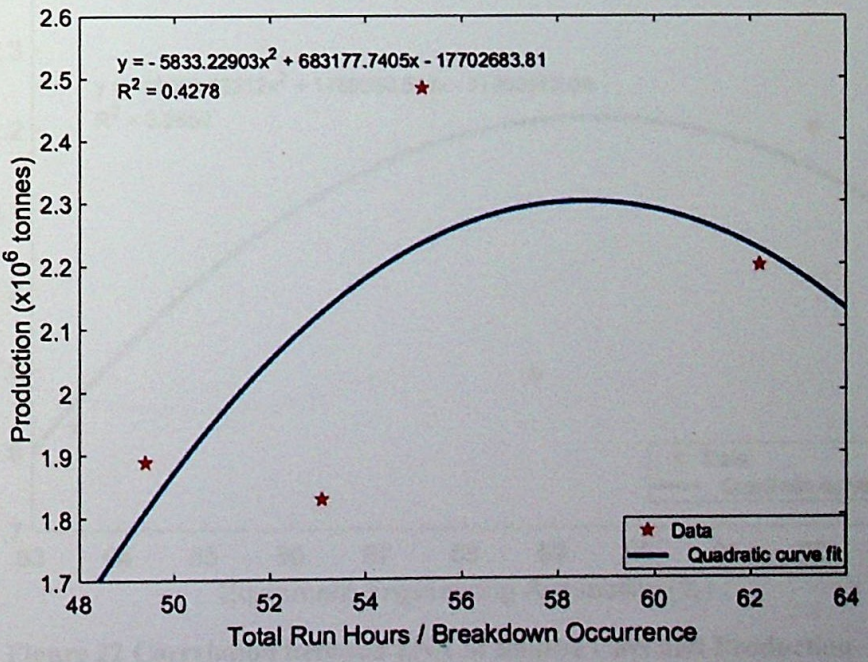


Figure 20 Correlation between MTBF of Shuttle Cars and Production

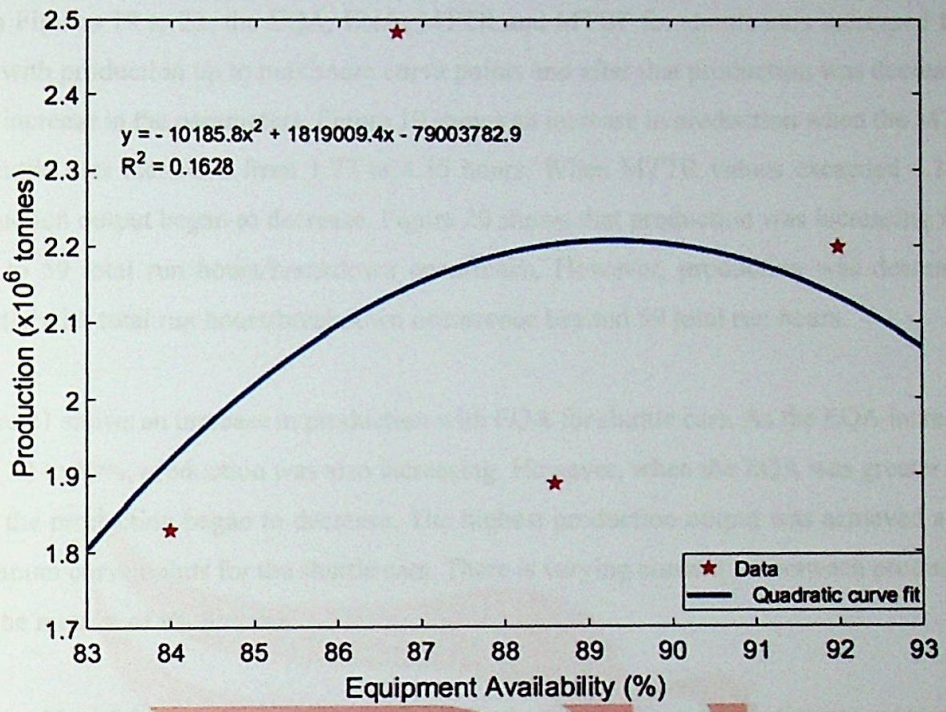


Figure 21 Correlation between EQA of Shuttle Cars and Production

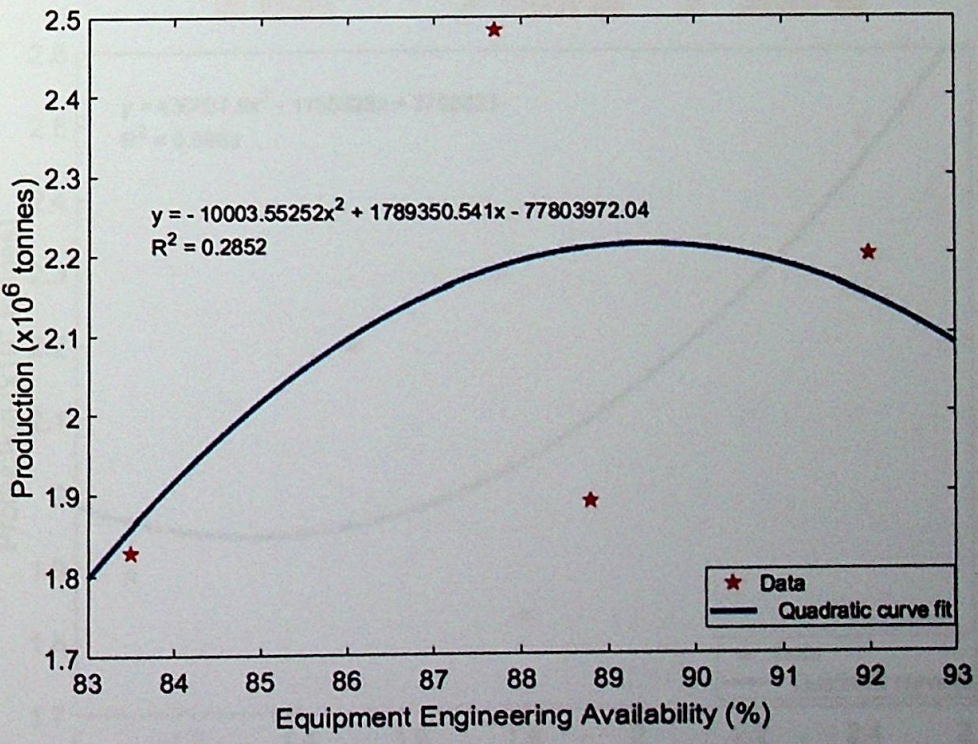


Figure 22 Correlation between ENA of Shuttle Cars and Production

From Figures 19 to 22, the EQA, ENA, MTTR and MTBF for shuttle cars increased from start with production up to maximum curve points and after that production was decreasing with increase in the parameters. Figure 19 shows an increase in production when the MTTR of shuttle cars increased from 1.77 to 4.35 hours. When MTTR values exceeded 4.35 hr production output began to decrease. Figure 20 shows that production was increasing from 48.4 to 59 total run hours/breakdown occurrence. However, production was decreasing directly with total run hours/breakdown occurrence beyond 59 total run hours.

Figure 21 shows an increase in production with EQA for shuttle cars. As the EQA increased from 83 to 89%, production was also increasing. However, when the EQA was greater than 89% the production began to decrease. The highest production output was achieved at the maximum curve points for the shuttle cars. There is varying correlation between production and the metrics of shuttle cars.

Figures 23 to 26 show the correlation between the performance of continuous miners and production output.

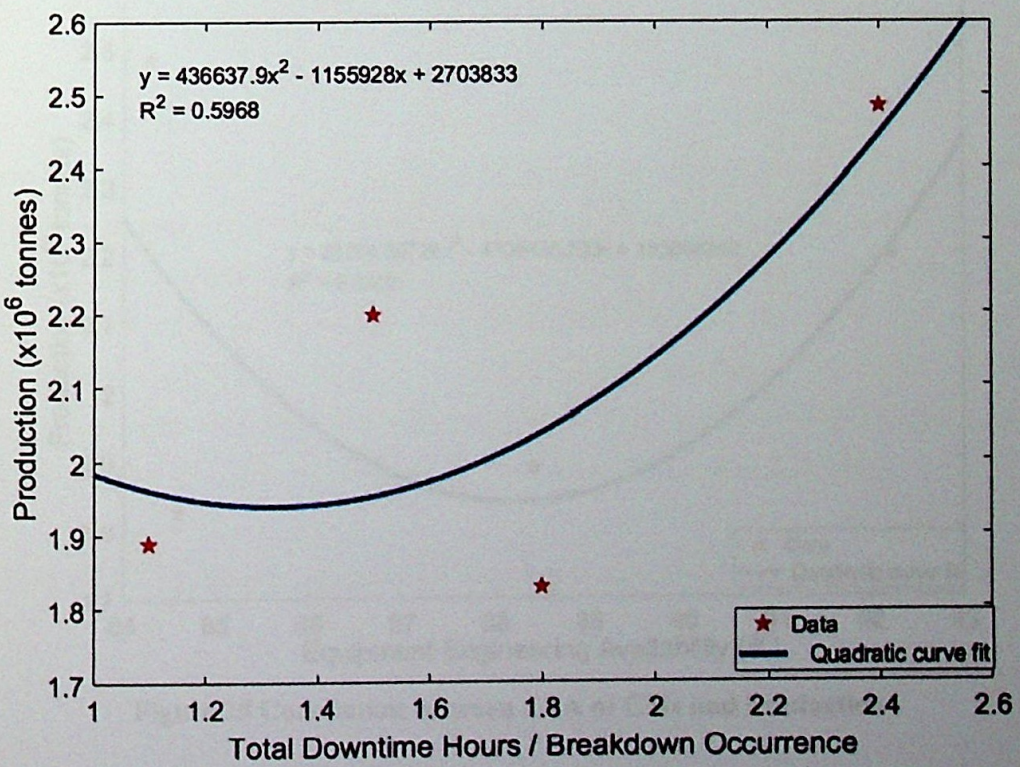


Figure 23 Correlation between MTTR of CMs and Production

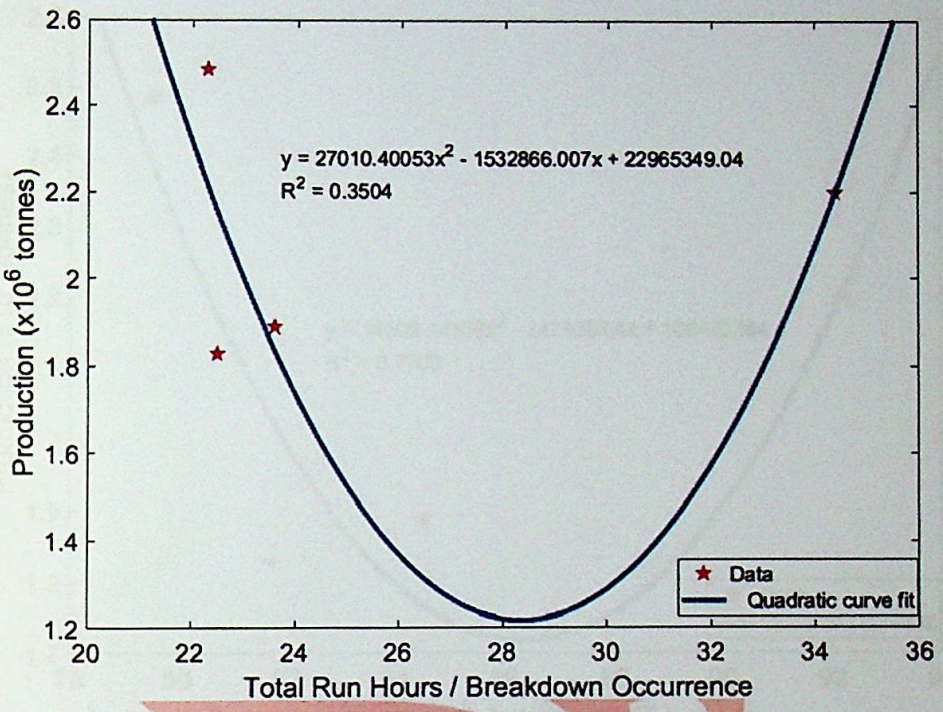


Figure 24 Correlation between MTBF of CMs and Production

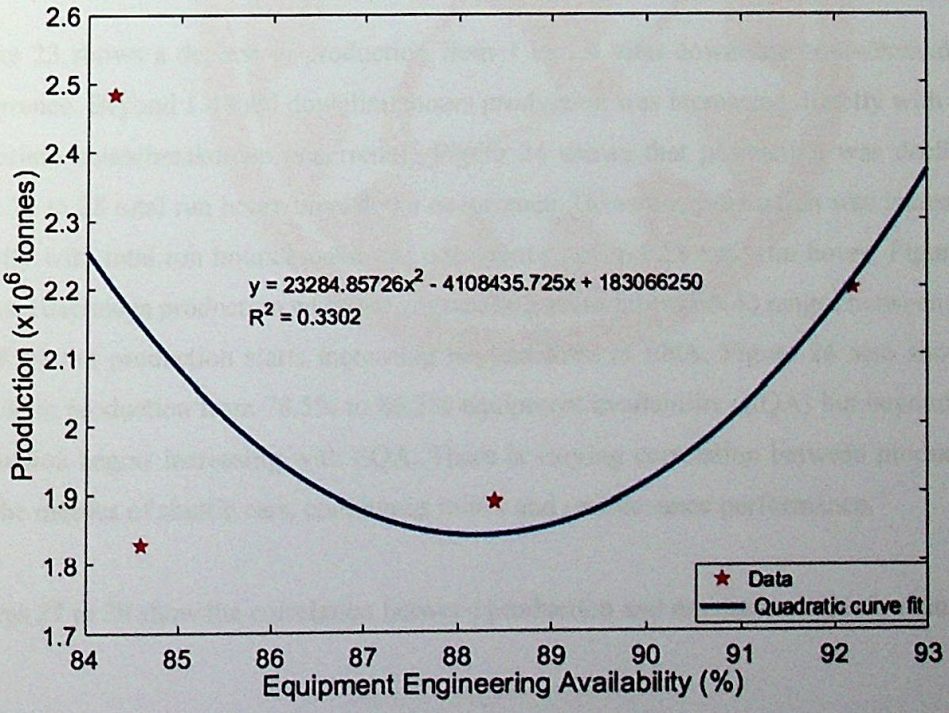


Figure 25 Correlation between ENA of CMs and Production

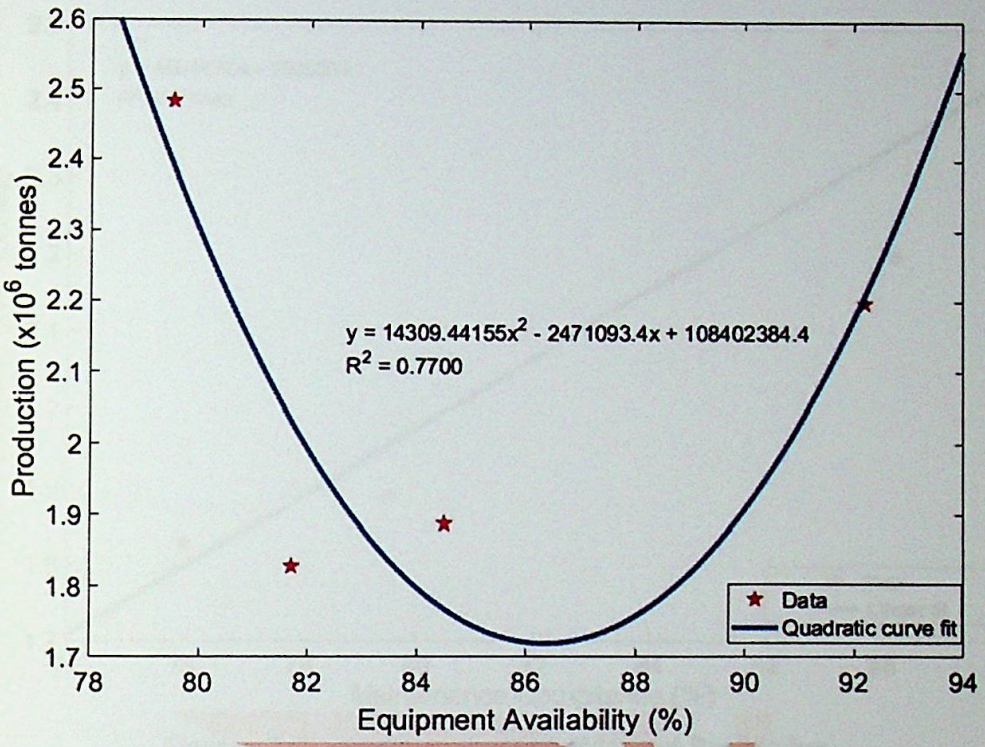


Figure 26 Correlation between EQA of CMs and Production

Figure 23 shows a decline in production from 1 to 1.4 total downtime hours/breakdown occurrence. Beyond 1.4 total downtime hours production was increasing directly with total downtime hours/breakdown occurrence. Figure 24 shows that production was declining from 21 to 28 total run hours/breakdown occurrence. However, production was increasing directly with total run hours/breakdown occurrence beyond 28 total run hours. Figure 25 shows a decline in production when the engineering availability (ENA) ranges between 84% and 87% but production starts increasing beyond 87% in ENA. Figure 26 also shows a decline in production from 78.5% to 86.5% equipment availability (EQA) but beyond that production begins increasing with EQA. There is varying correlation between production and the metrics of shuttle cars, continuous miner and maintenance performance.

Figures 27 to 29 show the correlation between production and maintenance performance.

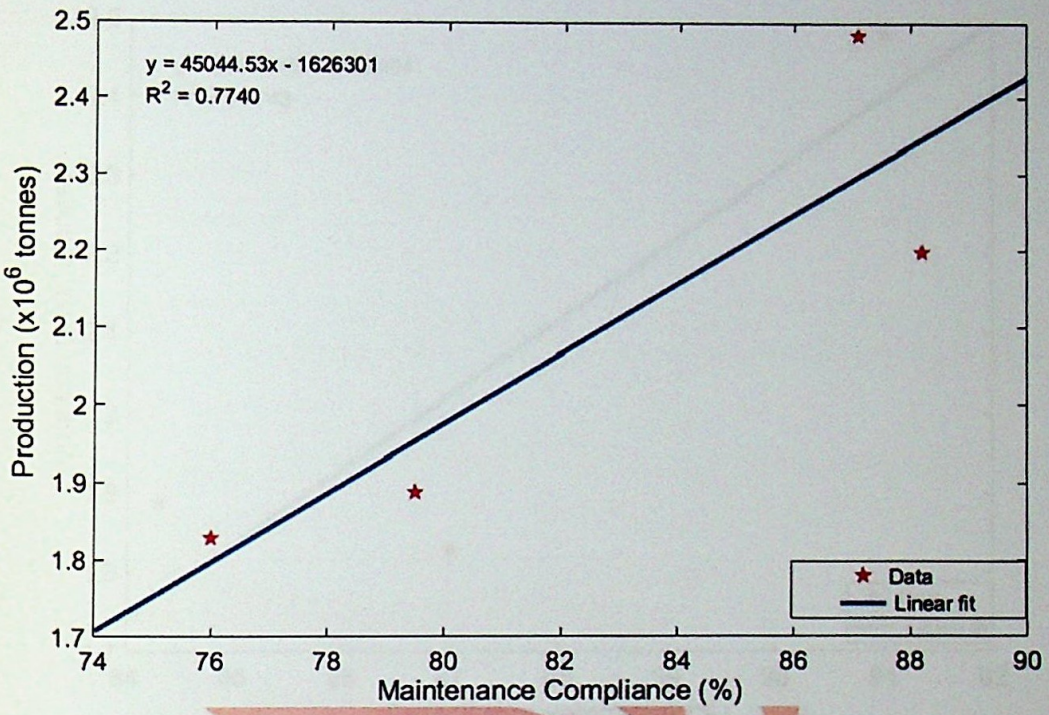


Figure 27 Correlation between UIMC and Production

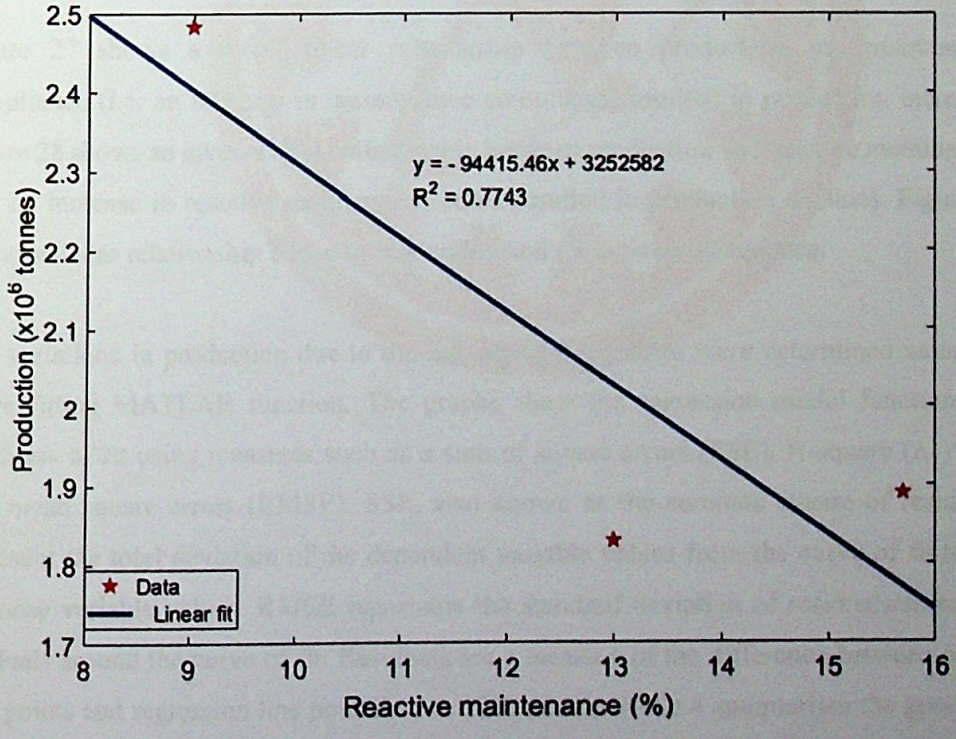


Figure 28 Correlation between Reactive Maintenance and Production

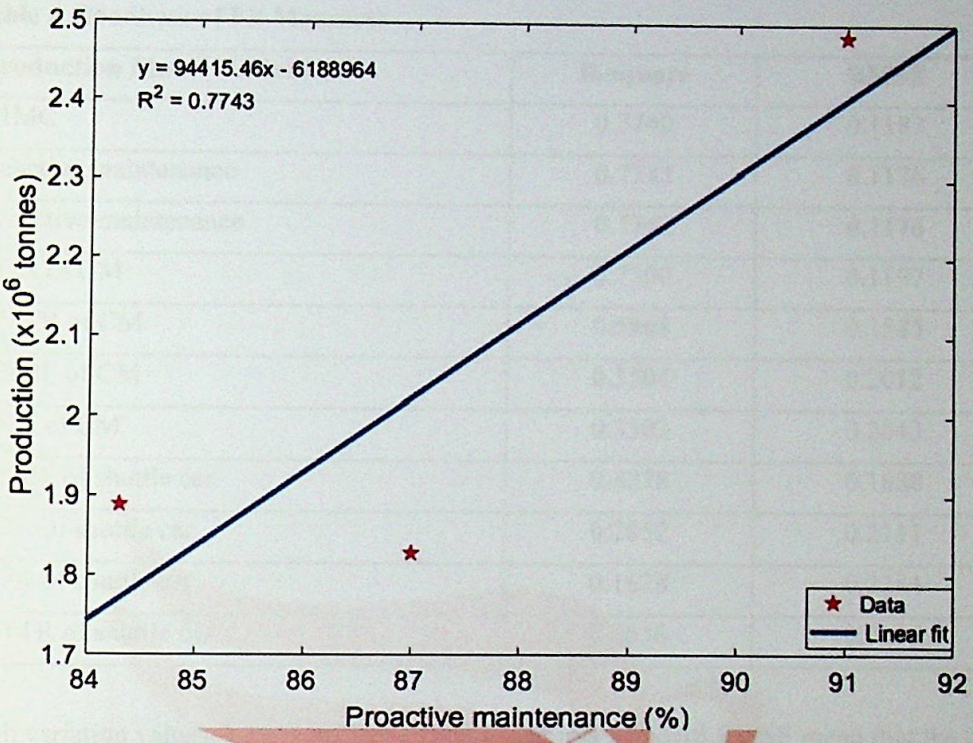


Figure 29 Correlation between Proactive Maintenance and Production

Figure 27 shows a direct linear relationship between production and maintenance compliance (i.e. an increase in maintenance compliance resulted in production increase). Figure 28 shows an inverse linear relationship between production and reactive maintenance (i.e. an increase in reactive maintenance cases resulted in production decline). Figure 29 shows a linear relationship between production and proactive maintenance.

The variations in production due to the independent variables were determined using the curve fitting MATLAB function. The graphs show the regression model function and goodness of fit using measures such as a sum of square errors (SSE), R-square $(r_{xy})^2$ and root mean square errors (RMSE). SSE, also known as the summed square of residuals, represent the total deviation of the dependent variable values from the curve of fit to the response variable values. RMSE represents the standard deviation of residuals/spread of residuals around the curve of fit. Residuals are a measure of the difference between actual data points and regression line points/curve of fit points. Table 4 summarises the goodness of fit results for the regression model/curve in terms of R-square and normalised RMSE for the various parameters.

Table 4 Goodness of Fit Measures

Production Model Variables	R-square	RMSE
UIMC	0.7740	0.1187
Reactive maintenance	0.7743	0.1176
Proactive maintenance	0.7743	0.1176
EQA of CM	0.7700	0.1197
MTTR of CM	0.5968	0.1585
MTBF of CM	0.3504	0.2012
ENA of CM	0.3302	0.2043
MTBF of shuttle car	0.4278	0.1888
ENA of shuttle car	0.2852	0.2111
EQA of shuttle car	0.1628	0.2284
MTTR of shuttle car	0.9636	0.0476

High variation values, high confidence bounds and low standard RMSE mean that the data points are close to the regression model curve points. This means the difference between actual data points and regression model curve points is small (i.e. residuals are small). Normalised RMSE values range from 0 to 1. The closer the values are to zero the better the model is. Residuals plots for the regression models in Figures 19 to 29 validate the models and the confidence limits for fitted coefficients are 95%.

The variables found to have impact on production performance by more than 70.00% were MTTR for shuttle cars (96.36%), EQA for CMs (77.00%), maintenance compliance (77.40%), reactive maintenance (77.43%) and proactive maintenance (77.43%). The regression model indicates a good fit for MTTR for shuttle cars, EQA for CMs, maintenance compliance, reactive and proactive maintenance and these variables have a strong strength of association with production performance.

The variables found to impact production performance by ≤ 70.00% were MTTR for CMs (59.68%), MTBF for shuttle cars (42.78%), MTBF for CMs (35.04%), ENA for CMs (33.02%), ENA for shuttle cars (28.52%) and EQA for shuttle cars (16.28%). The regression model for MTTR for CMs indicate a moderately good fit for R-squared value between 50.00% and 70.00%. The regression models for MTBF for shuttle cars, MTBF CMs, ENA

for CMs, ENA for shuttle cars and EQA for shuttle cars indicates a low to moderate strength of association with production for R-squared value ≤ 50.00%.

4.3 DISCUSSIONS

The following trends were observed in the operations at MCM from 2017 to 2020:

1. Production fluctuated from 2017 to 2020 (see Figures 5 and 6). An average production variance of -8.92% was recorded from 2017 to 2020 with yearly production variances of 14.81% (2017), 7.66% (2018), -26.85% (2019) and -6.34% (2020).
2. There were higher production outputs during morning shifts than in the other shifts (see Figure 7). Production outputs during night shifts were generally minimal and only meant to supplement the production during morning and afternoon shifts to meet daily and monthly targets.
3. The average availabilities of shuttle cars were generally below the set threshold targets (see Figure 9). Shuttle cars and CMs had the lowest equipment availabilities among all equipment from 2017 to 2020.
4. The average engineering availabilities of the mining equipment were above the set threshold targets (see Figure 10). Only CMs and shuttle cars had low engineering availabilities from 2017 to 2020.
5. The CMs, which are critical production machinery, had MTBF values that were below the set threshold values compared to all the other equipment. This means the CMs broke down more often than the other equipment (see Figure 13).
6. Shuttle cars had high MTTR values which means that they had longer downtimes per equipment breakdown (see Figure 14). Shuttle cars exceeded the set minimum times for a rapid/immediate repair to continue production operations in 2018 and 2019.
7. Reactive maintenance increased from as low as 9.0% in 2018 to 15.7% in 2020 (see Figure 15). Reactive maintenance cases were gradually increasing per year.
8. Production output per shift varied significantly from 2017 to 2020 (see Figure 16). Higher output per shift were achieved in 2017 and 2018 than in 2019 and 2020.
9. There was a decrease in underground inbye maintenance compliance performance from 2017 to 2019 and slight increases from 2019 to 2020. Maintenance

compliance threshold targets were not achieved, and this was due to the increase in issued maintenance work orders over the period (see Figure 17).

10. Variations/fluctuations in the performance of CMs, shuttle cars and maintenance performance led to a polynomial and linear relationships between the equipment availabilities and production output (see Figures 19 to 29).
11. The reactive and proactive maintenance, EQA for CMs, MTTR for shuttle cars and maintenance compliance influenced production outputs by 77.00% to 96.36%. This indicates a good fit for the model and strong correlation between the variables and production performance.
12. The MTTR for CMs influenced production performance by 59.68%. This shows a moderate fit for the regression model and moderate strength of association between the variables and production performance.
13. The ENA and MTBF for CMs and EQA, ENA and MTBF for shuttle cars had < 50% impact on production output. This shows the low strength of association between the variables and production output.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

It is concluded that:

1. The equipment availabilities for CMs were low ranging from 79.5% to 92.2% (with an average of 84.5%) and those for shuttle cars were high (ranging from 84% to 92.0%). The average EQAs of the equipment were higher than their set threshold targets except for CMs.
2. The engineering availabilities for CMs and shuttle cars averaged 87.4% and 88.0% respectively. These were higher than their set threshold targets but were the lowest performing machinery.
3. The MTTR values for shuttle cars were high (ranging from 1.9 to 6.9 downtime hours with an average of 3.7 downtime hours per breakdown) while the MTTR values for CMs ranged from 1.1 to 2.4 downtime hours with an average of 1.7 downtime hours per breakdown.
4. The actual run hours per breakdown for MTBF values of CMs varied from 14.7 to 25.9 with an average of 21.7 running hours per breakdown.
5. There was high reactive maintenance of more than 10% (or decreasing proactive maintenance performance for underground inbye operations) over the period 2015 to 2020.
6. There were wide variances in the production outputs between morning, afternoon and night shifts. The afternoon shifts generally had lower production outputs than the morning shifts. Production outputs during night shifts were generally insignificant but complemented the outputs from the morning and afternoon shifts to meet the daily and monthly production target.
7. The EQA and ENA of CMs and shuttle cars were generally low due to mechanical, fluid flow and electrical faults/breakdowns.
8. The variations in production outputs of CMs and shuttle cars were not directly proportional to the variations in maintenance performance of shuttle cars and CMs.
9. The regression models show a high goodness of fit for reactive and proactive maintenance, MTTR for shuttle cars, EQA for CMs and underground inbye

maintenance compliance. These variables impacted production performance significantly by 77.00% to 96.36%. This means that there is a strong correlation between these variables and production performance.

10. The MTTR for CMs influenced production output by 59.68%. The MTBF and ENA for CMs, MTBF, ENA and EQA for shuttle cars impacted production output by < 50.00%.

5.2 Recommendations

From the analysis in this work, it is recommended that:

1. The efficiency and effectiveness of shift teams should be measured regularly to know the contribution of each production team towards the production targets of the company. This will boost shift performance and improve overall production performance.
2. A computerised maintenance management system should be employed for real data metric analysis. This will ensure effective and efficient equipment maintenance control and management.
3. Technological advances should be adopted and integrated into the production system to respond immediately to problems with production units and improve the entire production system.
4. Shuttle cars should be frequently examined within their equipment reliability periods (using their current MTTR values) to maximise equipment uptime (MTBF values).
5. Reactive maintenance cases should be reduced from > 10.0% to at least 90.0% of proactive maintenance cases by employing total productive maintenance strategies. This will aid in increasing the UIMC performance as corrective maintenance issued work orders will be reduced.

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